Machines and Algorithms

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Editorial

Volume 3 Issue 2

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From the Editor

I feel pleasure in publishing this issue of the Machines and Algorithms journal, which is designed by keeping in view the interests of the audience in the theoretical and applied fields of Computer Science, i.e., Artificial Intelligence, Machine Learning, Generative AI, Image Processing, Algorithmic Optimization, Blockchain, Smart Environment, IoT, Quantum Computing, Distributed and Parallel Computing, Ubiquitous and Pervasive Computing, and other cutting-edge technologies that shape the future of computing.

In this issue, high-quality research articles are carefully compiled after a thorough peer-review process. We extend our gratitude to the authors for their valuable contributions and to the reviewers for their diligent efforts in maintaining the journal's academic rigor. A shorts overview of the papers included in this issue is given below.

The “Artificial Intelligence and Machine Learning in Hospital Waste Management” explores the integration of Artificial Intelligence (AI) and Machine Learning (ML) in hospital waste management, highlighting their potential to transform traditional practices. A systematic literature review was conducted using databases like PubMed, Scopus, and Web of Science, yielding 50 relevant articles from 2020–2023. The new feature is in describing AI/ML applications include intelligent monitoring via IoT, predictive analytics for waste generation forecasts, and automated waste sorting using CNNs. These developments increase sustainability, lower human error, and raise classification accuracy. Results indicate that kernel-based and neuron-based models outperform traditional methods in accuracy and efficiency. The paper also addresses key limitations such as data privacy, lack of annotated datasets, and integration issues with legacy systems. Future directions include developing advanced algorithms (e.g., federated learning and GANs) and integrating AI with IoT and blockchain to enable real-time tracking, data transparency, and scalable deployment in healthcare facilities.

The “Selecting Suitable Requirement Elicitation Technique for Development Methodologies” paper introduces a novel, systematic approach for selecting requirement elicitation techniques (RETs) tailored to specific software development projects. Unlike traditional arbitrary selection based on past experience, the proposed method leverages both qualitative and quantitative analyses, primarily using multiple linear regression and classification models to identify key project attributes influencing RET choice. The methodology involves gathering requirements from different domains, selecting significant project, people, and product attributes, and applying regression analysis to predict the most appropriate elicitation methods. The framework supports a variety of development methodologies, including web-based, mobile, and desktop projects. Results demonstrate that techniques such as interviews, focus groups, workshops, observation, and prototyping are optimal depending on project type and constraints. The study highlights the potential for future incorporation of machine learning and AI to enhance selection accuracy and adaptability, addressing current gaps in automated, context-aware elicitation techniques. This method decreases reliance on opinion and strengthens both requirement clarity and comprehensive content.

The "A Data-Driven Study of Mental Health Trends in the Tech Industry: Statistical and Machine Learning Perspectives" project offers a comprehensive data-driven analysis of mental health trends in the global IT sector by means of statistical methods and machine learning models.The research approach integrates data exploration with feature modification alongside predictive modeling to determine mental health influences on information technology workers that include worker demographics and both personal and working environment factors. The research stands out by analyzing mental health data across multiple countries together with workforce behaviors regarding treatment-seeking hence identifying major demographic and regional patterns which show higher treatment participation in New Zealand and Australia. A new predictive system employs Naïve Bayes classifiers because they analyze ROC curves and confusion matrices to successfully diagnose mental health issues while monitoring workplace mental well-being. The research recommends solutions through a dual focus on efficient model performance that enables workplace leaders to detect and create supportive environments for employee mental health in the stressful tech industry.

The study "Rule-Based Capitalization Algorithm Using NLP for Text Formatting Consistency" demonstrates use of NLP techniques with rule-based capitalization to achieve consistent text formatting within books and academic works and headlines. NLTK and SpaCy tools enable the system to separate words into two categories including notional types (nouns, verbs and adjectives) and non-notional categories (articles and prepositions) through tokenization and part-of-speech (POS) tagging. The program follows linguistic accuracy while its programmed rules ensure the correct formatting in title case. The system uses NLP with pre-programmed reasoning guidelines to pursue exact capitalization with greater success than generic heuristic approaches and online translation tools. The research findings demonstrate high accuracy which was verified through the assessment of precision, recall and F1 score indicating low error rates in system performance. A confusion matrix assessment and feature importance inspection demonstrate that system reliability happens through text reconstruction processes along with exception handling mechanisms. This paper describes how text reconstruction along with exception management leads to improved algorithm performance and affects automated publishing and content standardization.

A comprehensive breakdown of false news detection through machine learning (ML) and natural language processing (NLP) techniques exists in the "Fake News Detection using NLP and ML Techniques" paper that analyzes the Kaggle dataset of 40,000 news stories. The paper incorporates Naïve Bayes and Decision Trees alongside Random Forest with ensemble models XGBoost and CatBoost alongside neural network component LSTM as key ML Algorithms. This research presents the main outcome through a performance analysis which confirms ensemble learning algorithms and deep learning methods outperform traditional classifiers when measuring accuracy and recall rates. The validation results of XGBoost achieved 92% while CatBoost demonstrated strong recall capabilities which establishes their effectiveness in identifying false news. The research reveals that TF-IDF vector extraction overcomes simple tokenization as a necessary feature extraction technique. Through systematic algorithm assessment the paper both advocates a successful NLP-ML hybrid method and presents future directions for false news detection enhancement through different feature representations and validation techniques which enhance the field of knowledge.

Our team is highly committed and works hard to ensure that Machines and Algorithms continues to publish quality research articles. Looking ahead, we aim to expand the journal's reach, collaborate with leading research institutions, and introduce special issues on emerging topics. Your feedback and participation are invaluable in shaping the future direction of Machines and Algorithms.

Thank you for your continued support. We hope this issue meets your expectations.

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Research Article

A Data-Driven Study of Mental Health Trends in the Tech Industry: Statistical and Machine Learning Perspectives

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Abstract: Mental wellbeing is critical for people to survive in the fast-paced workplace of today in order to succeed both personally and professionally. The computer sector poses particular difficulties for mental health because of its intensive work ethic, long hours, and high levels of stress. Research by Open Sourcing Mental Illness (OSMI) has shown that mental health disorders are especially prevalent in the technology sector. This study aims to identify important elements and facilitate early detection through a comprehensive analysis of mental health trends in the tech sector. This paper looks at the frequency of mental health problems among technical professionals in comparison to their non-technical counterparts using the Mental Health in Tech survey dataset, collected from people all around the world. Using rigorous statistical analysis and predictive modelling, the study explores variations in the frequency of mental disorders across different geographic locations and examines workplace attitudes towards mental health. The study combines a Python-based approach comprising feature engineering, exploratory data analysis, data preparation, and machine learning model building to forecast mental health diagnoses. The findings of this study highlight important mental illness and treatment-seeking attitude determinants as well as the prevalence of mental health problems in tech-related companies. This study aims to help create work environments that give mental health a top priority by elucidating effective strategies for promoting worker well-being and encouraging help-seeking behavior.

Keywords: Predictive Mental Health; Workplace Wellness; AI in Mental Health; Machine Learning; Mental Health Risk; Work-Life Balance;

1. Introduction

Our mental health is the emotional, psychological, and social well-being we have that shapes our relationships with others, our job performance, and our physical health maintenance. The IT industry, famous for its great stress levels, long work hours, and great drive to succeed, is coming under closer examination for how these elements influence employees' mental health. The World Health Organization (WHO) has highlighted how prevalent stress and strain at work are in technical sectors and how such factors can lead to significant loss of production and job churn [1, 2]. Because employees are often younger and have been subjected to lengthy workdays, the computer sector is more likely to experience burnout and a bad work-life balance [3]. The tech sector's fast expansion highlights the need to handle workplace elements influencing mental health, with more than 53.2 million full-time workers in 2019 and a projection to reach 62 million by 2023 [4, 5].

Though mental health problems are common, many people wait a long time to get help—an average of ten years before consulting a general medical practitioner and much longer before seeing a psychiatrist [6]. Untreated mental health problems might get worse with time; hence, early diagnosis and treatments are quite vital [7]. A staggering 51% of tech professionals have been diagnosed with a mental health condition, and 57% report that their productivity is affected by mental health issues [8, 7].

Tech workers are five times more likely to suffer from mental health problems compared to other sectors, with stress, anxiety, and depression being prevalent [9]. The long-hours culture and the pressure to excel contribute to this trend, leading to severe physical symptoms like headaches, sleep deprivation, and anxiety attacks [10]. The stigma surrounding mental health in tech is a significant barrier to seeking help. Many employees fear job security and judgment from colleagues, with 38% concerned about speaking up and 17% worried about-facing prejudice [11]. Almost a quarter of tech workers lack official protocols for addressing mental health concerns within their teams, and 65% feel that physical health issues are given less prejudice than mental health issues [12].

Machine learning is being used to help diagnose mental health problems. This special tool can look at complicated patterns that have to do with how people are feeling and can guess better who might have mental health issues. Because machine learning uses a lot of data, doctors can find out sooner if someone has a mental health problem. It can also tell us trends about mental health in workplaces. For our project, we're using different kind of machine learning strategies. These let us identify the main causes of mental health problems in the world of technology. With this, we can get a better idea of mental health patterns, find out faster who might have problems, and help create plans to support the health of workers before problems come up.

The rest of the paper is organized as follows. In Section 2, previous work defining the impact of long working hours in mental well-being is presented. In section 3 methodology for mental health wellbeing analysis is presented. Results of the analyzed models is presented under section 4, while section 5 concludes our work.

2. Literature Review

A wide range of research and programs focusing on comprehending, avoiding, and managing mental health problems among employees are together referred to as mental health in the workplace. Memish et al. (2017) carried out a systematic study to assess the standard and scope of employer-developed recommendations for handling mental health issues at work. In order to translate scientific data into useful suggestions for averting mental health problems at work, this review conferred with specialists in psychology, public health, and mental health promotion [11].

Kahn et al. (2003) offered a thorough manual for identifying, comprehending, averting, and addressing mental health problems in individuals and organizations at work. In addition to emphasizing the availability of high-quality mental health care, their work focuses on developing corporate productivity and employee mental health through the development of systems and cultures [12].

In 2009 Chopra et al. examined how productivity at work affects people's physical and mental health, especially in developing nations. Their research demonstrated the connection between workplace stress and the rise in prevalent mental illnesses, highlighting the necessity of studies on mental health promotion and intervention to enhance worker productivity and well-being [13].

In 2020 Sasaki et al. looked into the relationship between Japanese employees' mental health and productivity and workplace policies put in place in response to COVID-19. The impact of organizational responses to the pandemic on employee well-being was illuminated by their study, which found strong relationships between workplace measures, psychological distress, fear and worry related to COVID-19, and work performance [14].

Eaton et al. (2018) claim that because mental health issues get insufficient worldwide focus, society must address stigma around mental illness. Their study objective was twofold: first, to raise workplace awareness of mental health practices; second, to develop workplace projects supporting a health workplace environment by means of techniques preserving and strengthening worker mental health. Latest research uses machine learning tools on mental health analysis to find disorders as well as assess susceptibility to such conditions. Examining COVID-19 epidemic impacts on workplace mental health, associations investigated stress elements as well as employee stress patterns.

Diverse literature review investigating several preventative and treatment strategies for worker mental disorders reveal how mental health interacts with workplace settings, according to the literature review. Studies indicate that companies who get the need for proactive actions supporting and improving employees' mental health also grasp the workplace relevance of mental health.

3. Methodology

We used the openly available dataset. The results led us by the provide important points for further action.

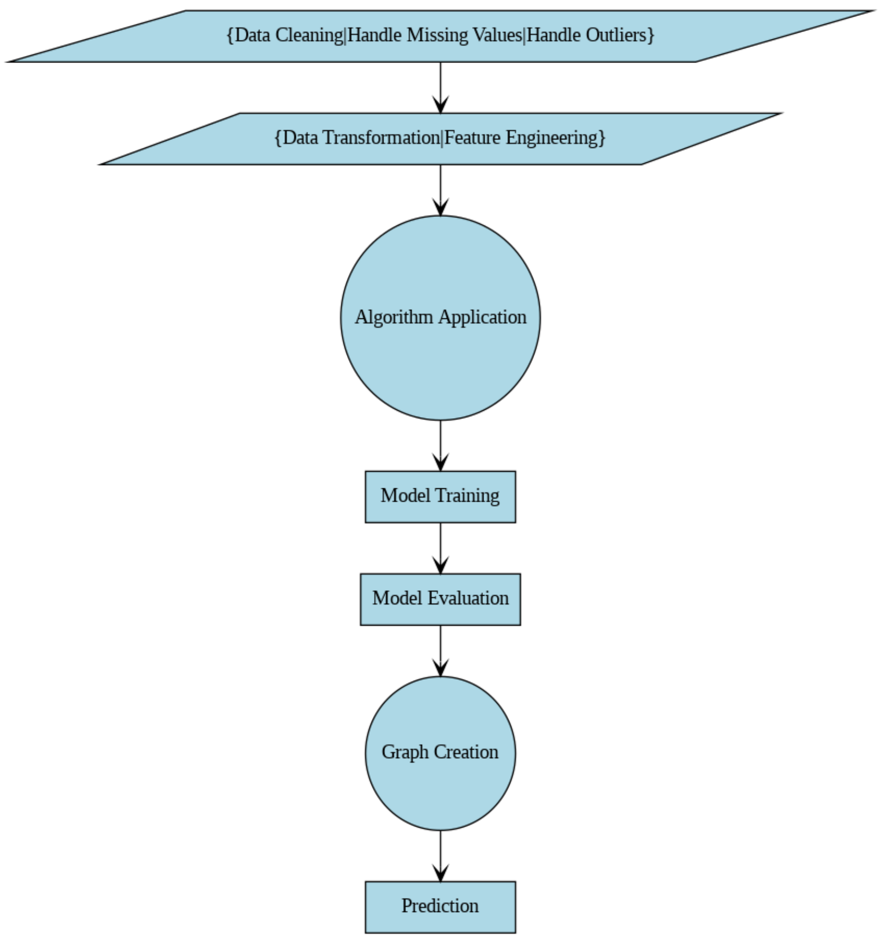

Figure 1: Methodology for Model Development and Prediction

3.1. Data Collection

The Open Sourcing Mental Illness (OSMI)—Mental Health in Tech Survey's 2016–2021 data were used in this study [16]. Approximately 1400 responses were gathered for 63 questions concerning employee mental health, attitudes toward mental health in the workplace, awareness of mental health, demographics, and other related topics. The purpose of the 2016 survey is to assess the attitudes toward mental health of tech employees and investigate the frequency of mental health issues among them. Comparably, the 2017–2021 OSMI Mental Health in Tech Survey data sets include 756 respondents, 417 in 2018, 352 in 2019, 180 in 2020, and 131 in 2021.

The data sets were utilized to analyze workplace culture trends, employee mental health situations, and the effects of COVID-19 on these areas.

Records	Features	Dataset Size
1259	27	296 KB

Id	Features	Description
01	**Timestamp**	Time the survey was submitted.
02	**Age**	The age of the person.
03	**Gender**	The gender of the person.
04	**Country**	The country name where person belongs to.
05	**state**	The state name where person belongs to.
06	**self_employed**	Is the person self employed or not.
07	**family_history**	Does the person's family history had mental illness or not?
08	**treatment**	Have you sought treatment for a mental health condition?
09	**work_intefere**	If you have a mental health condition, do you feel that it interferes with your work?
10	**no_employees**	How many employees does your company or organization have?
11	**remote_work**	Do you work remotely (outside of an office) at least 50% of the time?
12	**tech_company**	Is your employer primarily a tech company/organization?
13	**benifits**	Does your employer provide mental health benefits?
14	**care_options**	Do you know the options for mental health care your employer provides?
15	**wellness_program**	Has your employer ever discussed mental health as part of an employee wellness program?
16	**seek_help**	Does your employer provide resources to learn more about mental health issues and how to seek help?
17	**anonymity**	Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources?
18	**leave**	How easy is it for you to take medical leave for a mental health condition?
19	**mental_health_consequence**	Do you think that discussing a mental health issue with your employer would have negative consequences?
20	**phy_health_consequence**	Do you think that discussing a physical health issue with your employer would have negative consequences?
21	**coworkers**	Would you be willing to discuss a mental health issue with your coworkers?
22	**supervisor**	Would you be willing to discuss a mental health issue with your direct supervisor(s)?
23	**mental_health_interview**	Would you bring up a mental health issue with a potential employer in an interview?
24	**phs_health_interivew**	Would you bring up a physical health issue with a potential employer in an interview?
25	**mental_vs_physical**	Do you feel that your employer takes mental health as seriously as physical health?
26	**obs_consequence**	Have you heard of or observed negative consequences for coworkers with mental health conditions in your workplace?
27	**comments**	Any additional notes or comments.

Figure 2: Features Description

We have a situation where the 'state' field contains 40% missing values and 40% of the data comes from outside the US.

- It is noteworthy that the location of California, which is in the United States, is the mode for the 'state' field.
- Therefore, it wouldn't be appropriate to replace missing values in the 'state' column for different countries with 'California'.

3.2. Exploratory Data Analysis

A Series of questions to uncover patterns, trends, anomalies, relationships, and key insights without making any formal assumptions about the data.

- Q. What is the assosciation between Gender & Treatment?

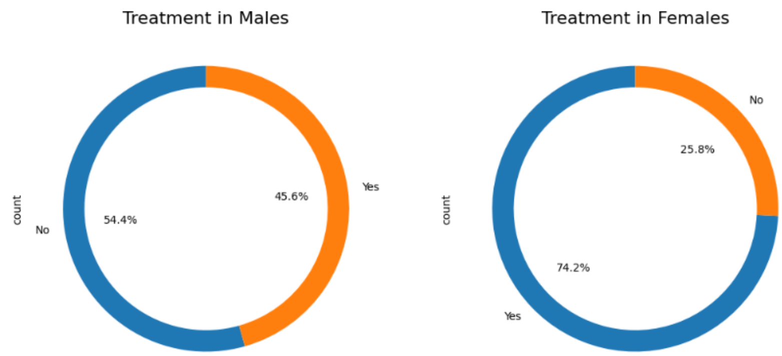

Figure 3: Association Between Gender and Treatment

Based on the data, it appears that individuals identifying as Females exhibit a higher tendency to seek treatment for mental health issues in comparison to Males. The statistics shows 48% of Males and 71% of Females have gone through treatment among the top 3 countries.

- Q. What is the association between treatment and work_interference?

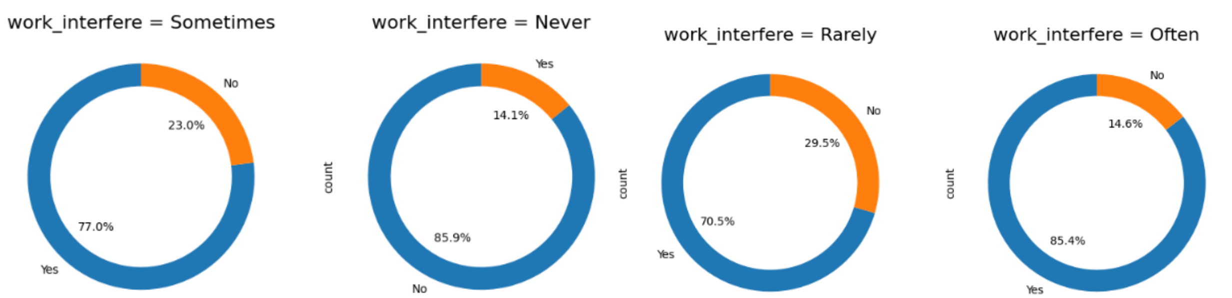

Figure 4: Association Between Treatment and work_interference

We can observe that employees who are more 'Often' & 'Rarely' interfered during work are likely to have Mental health issues and hence are seeking Treatment.

- Q. Do individuals show a greater willingness to seek treatment for mental health issues if there is a family history of such conditions?

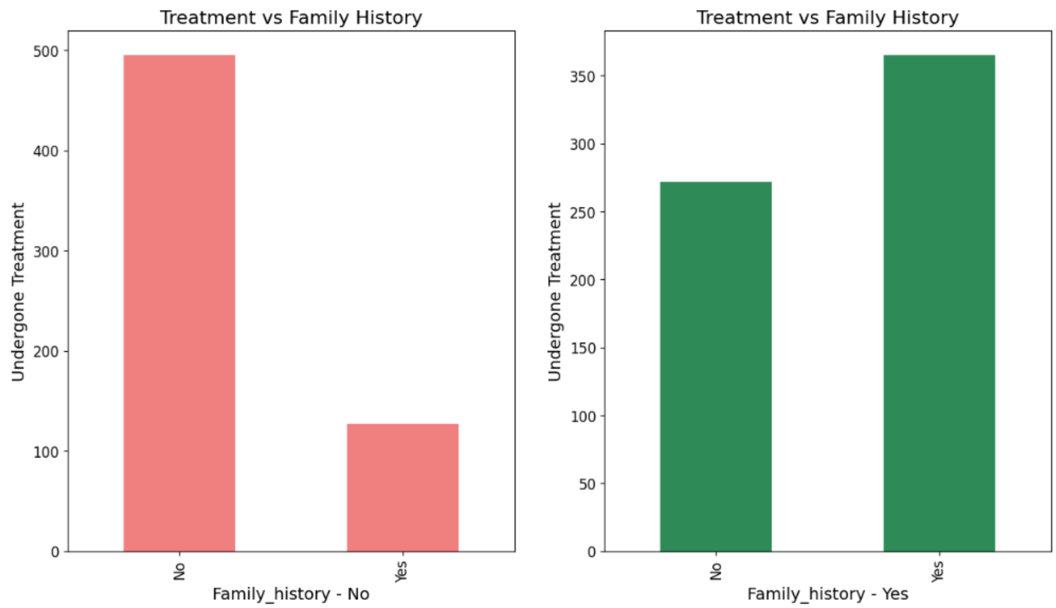

Figure 5: Association Between family_history and Treatment

We observe that employees with a family history of mental health issues are more inclined to choose treatment.

In contrast, employees without a family history of mental health issues may have lower awareness and, consequently, a reduced likelihood of seeking treatment.

- Q. What is the association between treatment and employee count in a company?

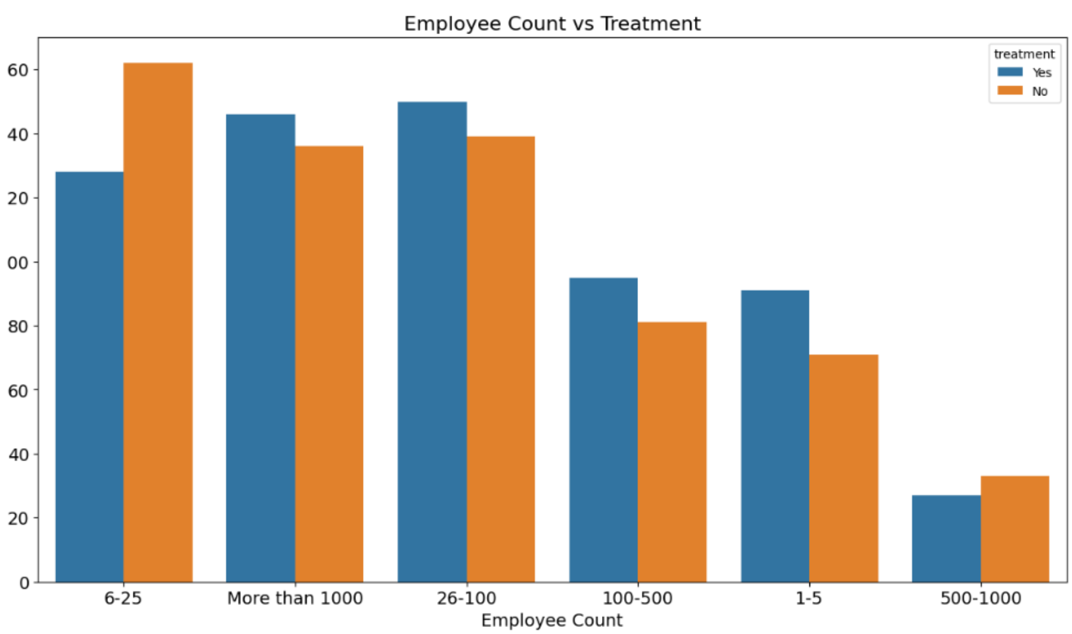

Figure 6: Association Between Employee Count in Company and Treatment

Based on the data, it can be inferred that the highest number of employees who sought mental health treatment belong to companies sized between 26-100 employees.

Conversely, the largest number of employees who did not seek treatment come from companies sized between 6-25 employees.

3.2.1. Data Set Analysis and Findings.

- Q. Top 10 Countries recorded for mental health treatment?

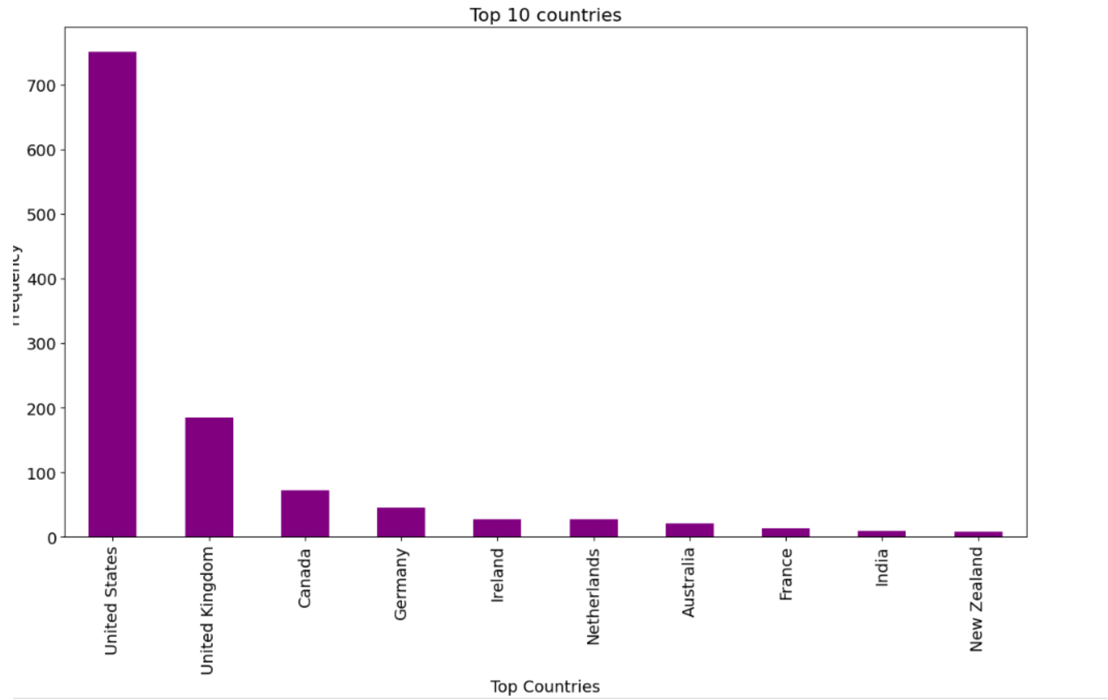

Figure 7: Country Wise Mental Wellness Treatment

The majority of the records are from the United States, followed by the United Kingdom and Canada.

- Q. Which countries are actually contributing more for mental health treatment?

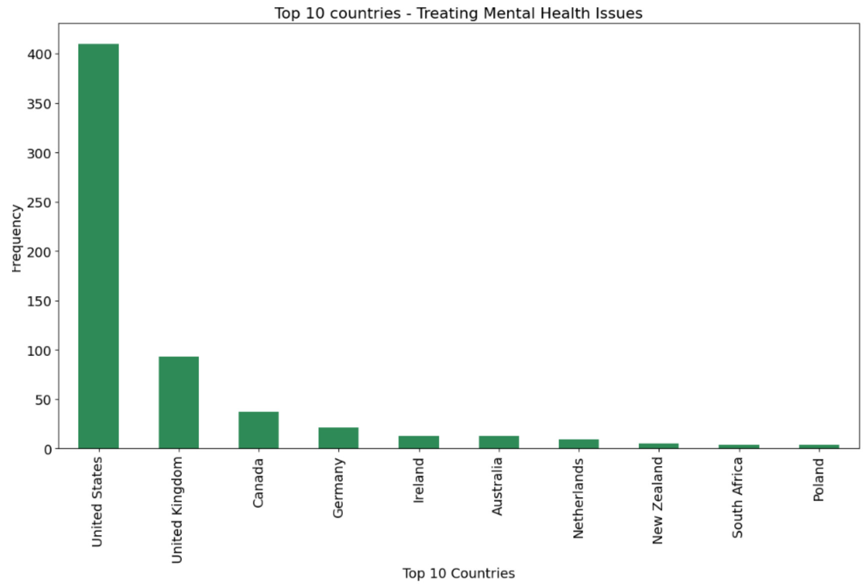

Figure 8: Country Wise Mental Issues Treatment

A change can be seen in the bar chart's lower portion, which shows the nations where more people are seeking mental health therapy.

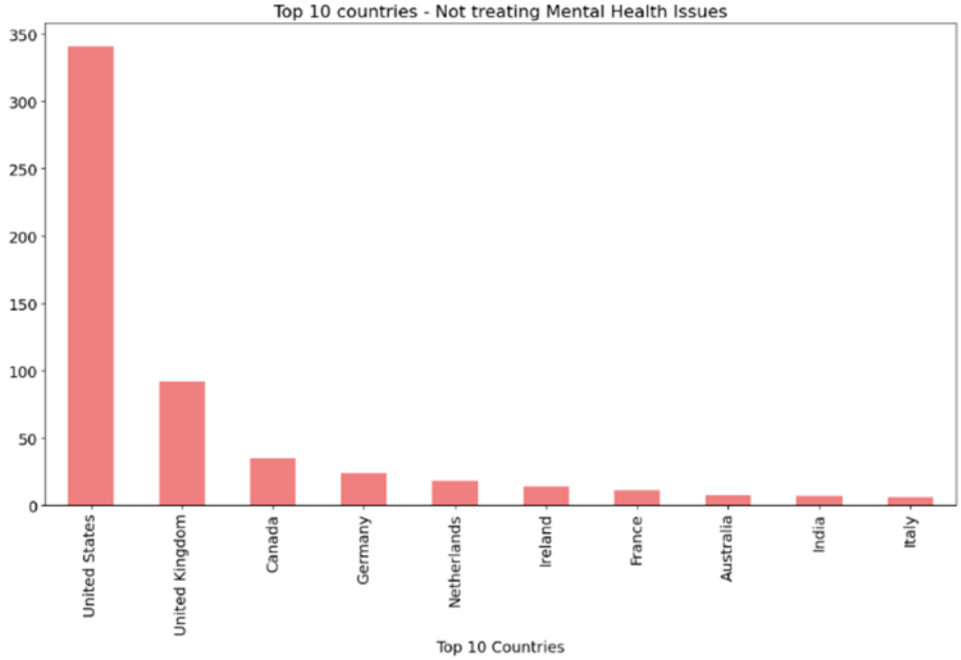

Figure 9: Country Wise Mental Issues Not Being Treated

Here are the Top 10 countries where individuals are least inclined to seek treatment for their mental health concerns.

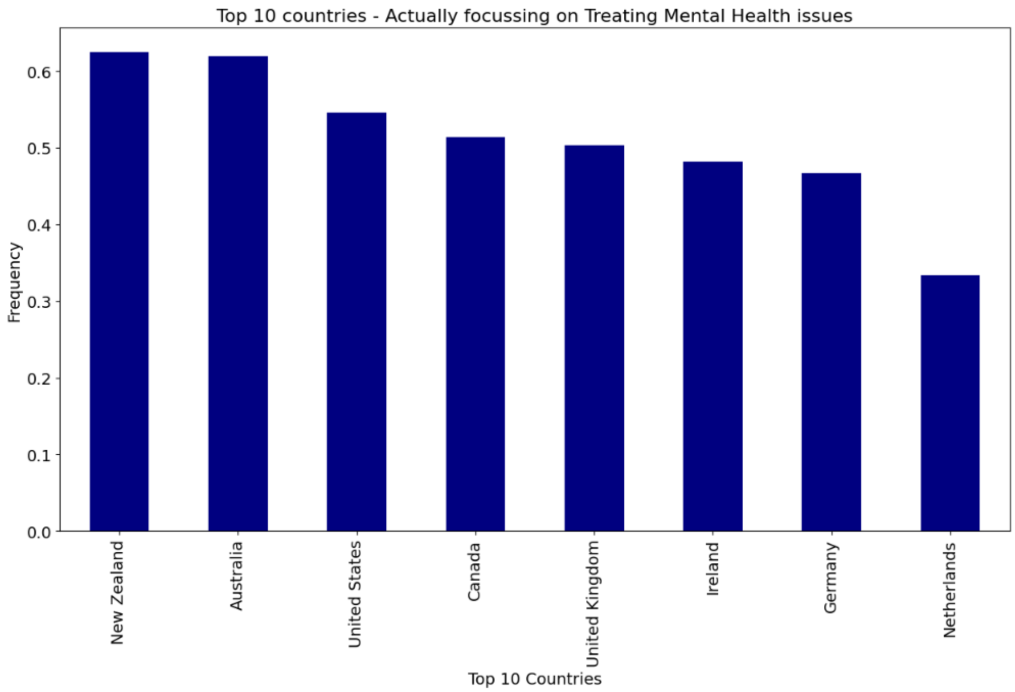

Figure 10: Top Countries Focusing Mental Health Wellness

According to the data, the top countries for both categories are the United States, the United Kingdom, Canada, and Germany, which treat a large number of people with mental health problems while also having the greatest incidence of untreated mental health cases. The inconsistency of our assertion is shown by this statistical contradiction.

To resolve the aforementioned paradox, let's conduct a comprehensive analysis focusing on the data distribution, specifically examining countries that meet the condition where Treatment equals 'Yes' out of the total values recorded.

3.2.2. Age vs Gender Distribution of Tech Company Employee

Let's calculate the ratio of observations from countries addressing mental health issues to the total number of countries included in the dataset shown in figure 10

These countries prioritize influencing a significant proportion of their population to address mental health issues, considering the total number of reported issues.

New Zealand & Australia top the list, followed by United States & Canada.

- Q. What is the frequency distribution of work interference among employees for the top 3 countries?

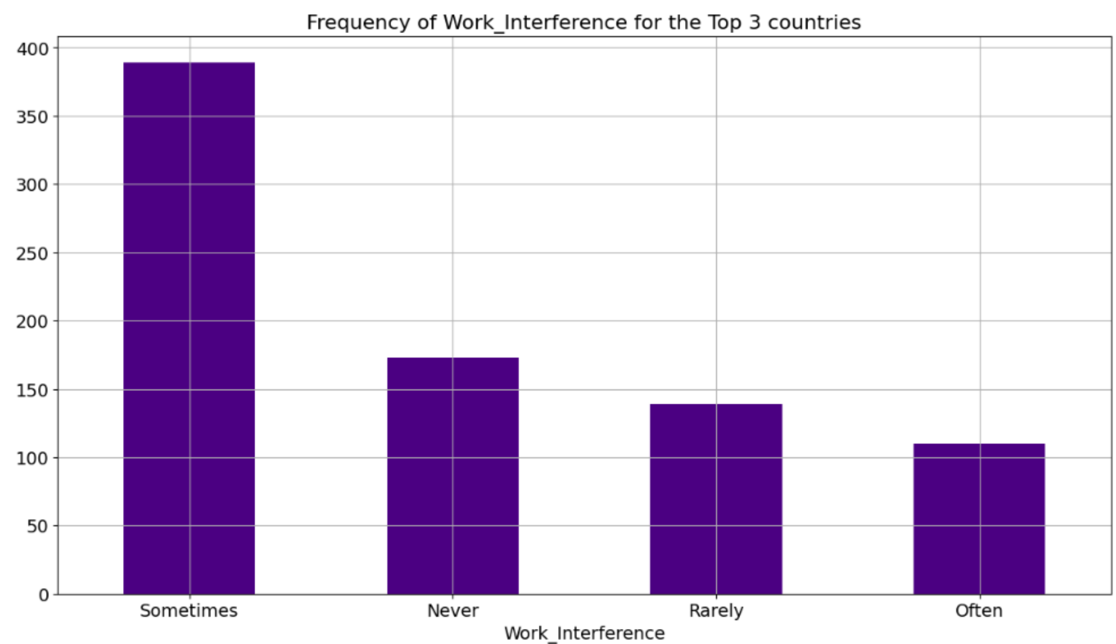

Figure 11: Work Interference Causing Mental Health Treatment

The majority of individuals seeking treatment for their mental health issues experienced interference with their work at times.

- Relation between Treatment and Mental Health Consequence?

mental_health_consequence - Do you think that discussing a mental health issue with your employer would have negative consequences

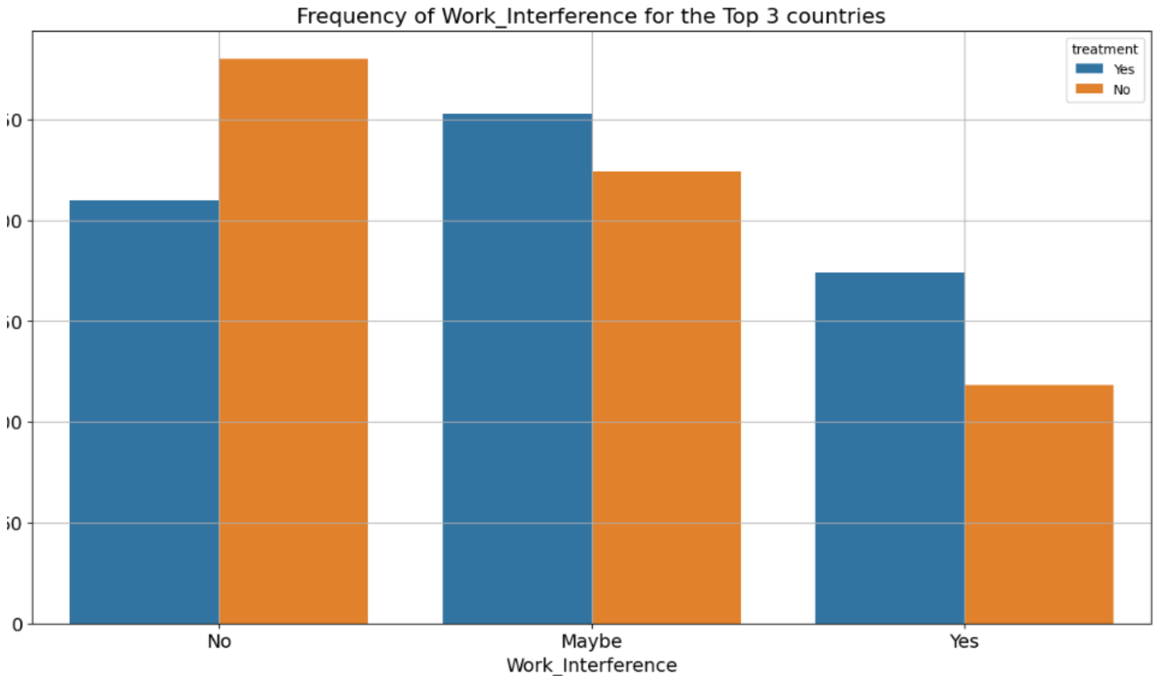

Figure 12: Top Countries of Work Interference

People who fear unfavorable outcomes from talking to their employers about mental health difficulties are more likely to seek help for their problems.

Comparably, people who feel at ease talking to their employers about mental health problems also typically have a decreased readiness to seek help for their worries.

- Q. What is the relationship between mental health consequences and the attitude?

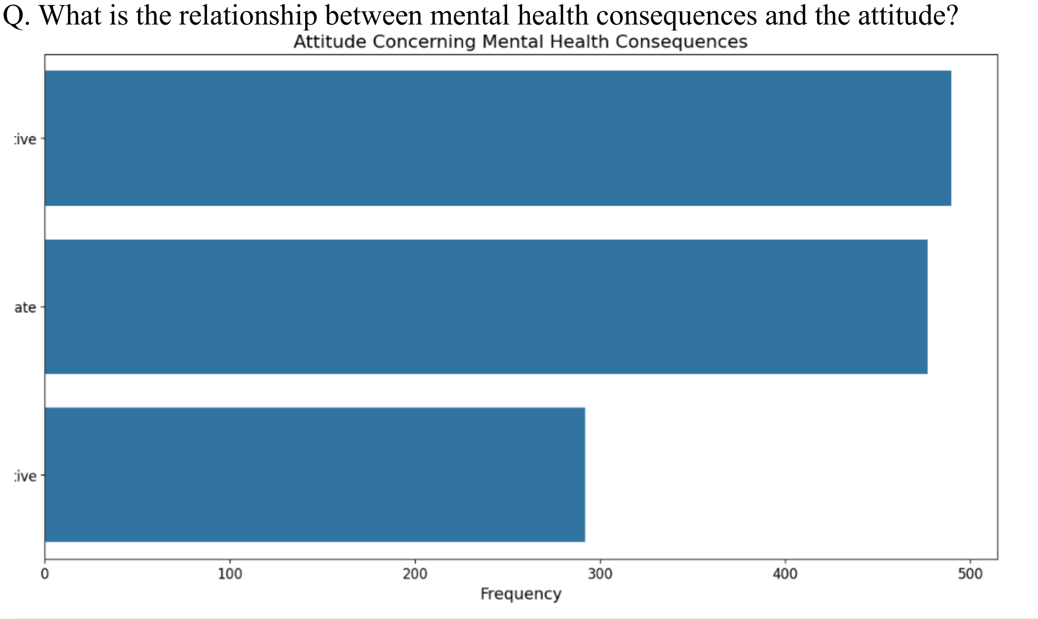

Figure 13: Attitude Affecting Mental Health

The majority of individuals perceive their employers' attitudes to be more positive or moderately supportive rather than negative when addressing their mental health concerns**.**

- Q. How does age relate to various behaviors and/or their awareness of their employer's attitude toward mental health?

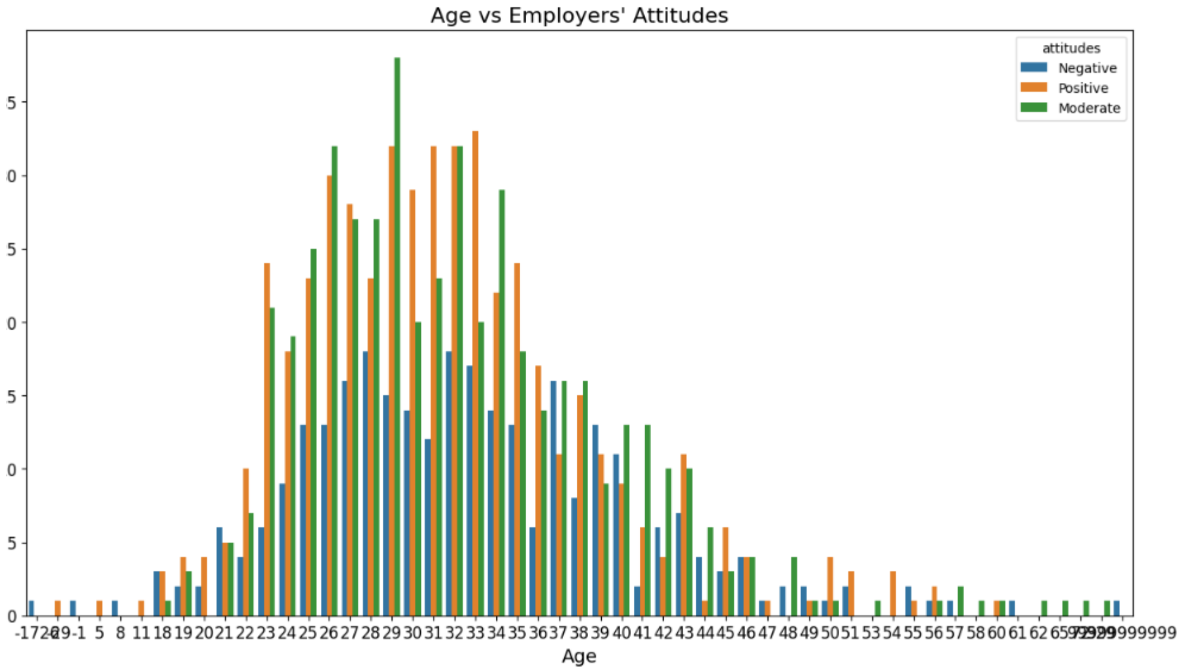

Figure 14: Age vs Employee's Attitude

This suggests that individuals in their mid-20s to mid-30s perceive their employers' attitude to be more positive or moderately supportive rather than negative when they discuss their mental health concerns.

3.2.3. Summarization

The mental health survey has helped us to understand the mental condition of employees working in tech firms across countries.

A total of 1259 entries were recorded during the survey out of which 1007 were recorded from the top 3 countries. The United States leads the chart in terms of participation in the survey followed by the United Kingdom and Canada.45% OF males, 69% of females, and 79% of trans were found to have sought treatment concerning the overall survey.

Likewise, data indicates that 48% of males, 71% of females, and 80% of trans individuals have received treatment within the top three countries in the recorded dataset. The following set of parameters are found to be affecting mental health the most and thus requires treatment:

- Age
- Family history,
- Work Interference,
- Number of employees working in a company,

New Zealand and Australia lead in prioritizing the resolution of employees' mental health issues, encouraging a higher number of individuals to seek treatment, followed by the United States and Canada.

The data shows a prominent peak occurring between the mid-20s to about mid-30s, indicating that the majority of individuals fall within this age range.

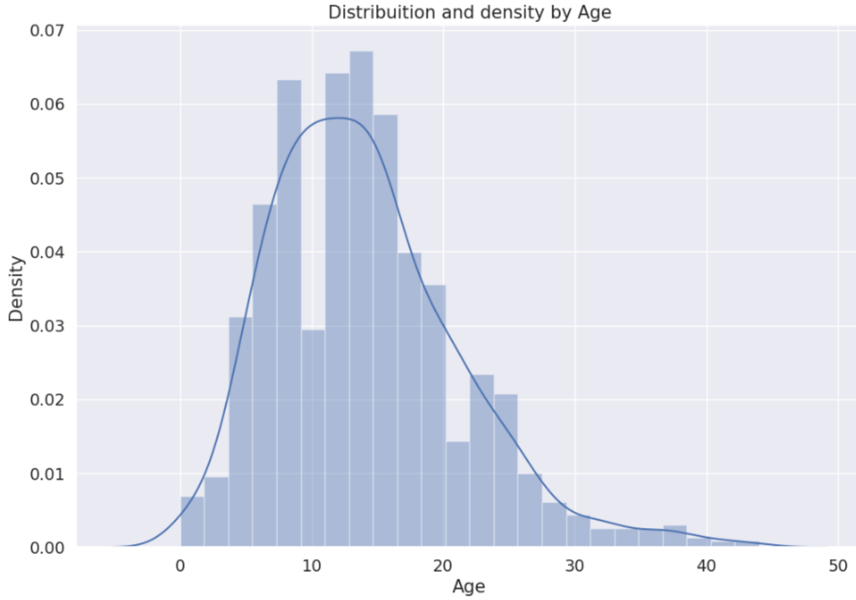

Figure 15: Data Distribution and Density by Age

Age groups demonstrate heightened awareness of their mental health. The dataset parameters and their graphical representations are displayed here.

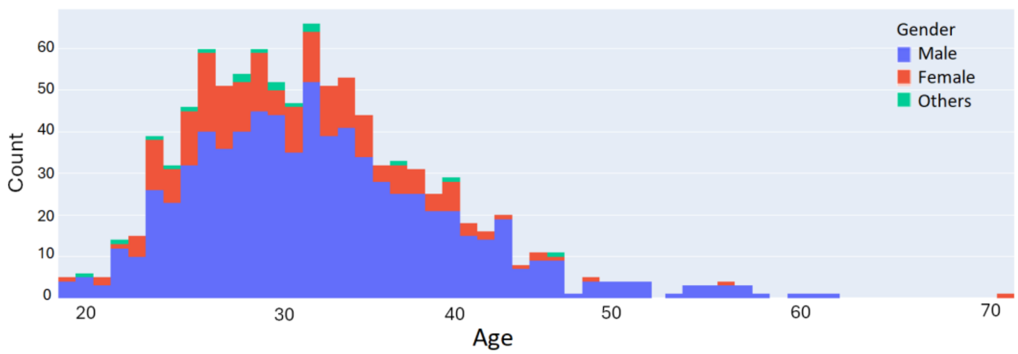

Figure 16: Mental Health Treatment by Age Group

3.2.4. Treatment by Age

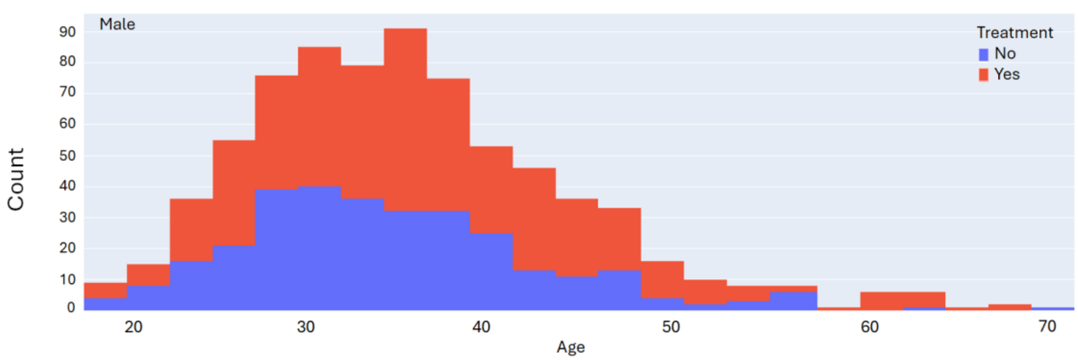

Figure 17(a): Frequency Distribution of Males Getting Treatment vs not-getting Treatment

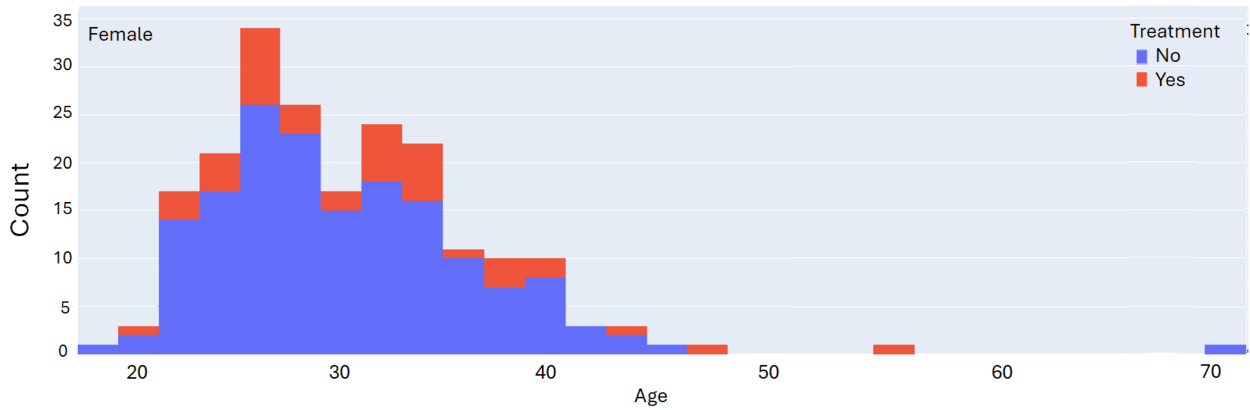

Figure 17(b): Frequency Distribution of Females Getting Treatment vs not-getting Treatment

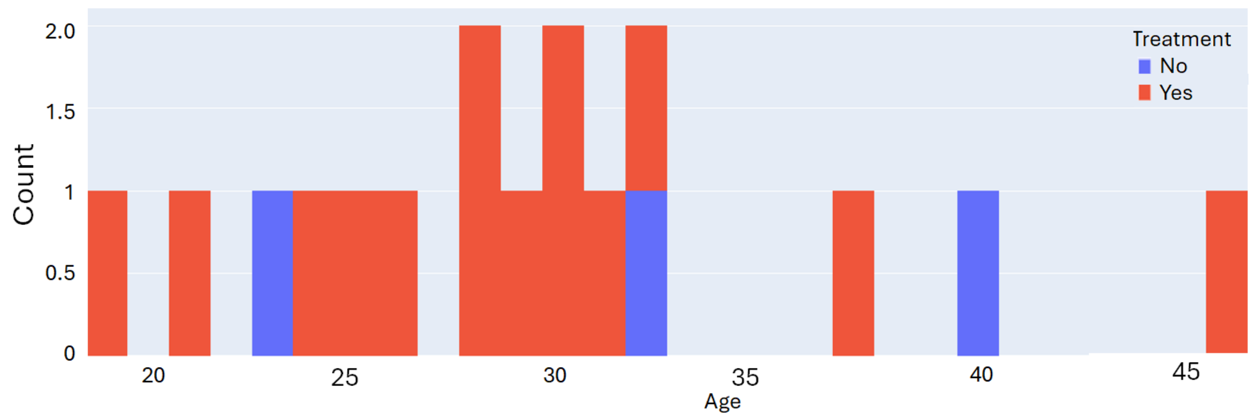

Figure 18: Age-wise Frequency Distribution of Other Gender Getting vs not-getting Treatment

Analyzing the proportions, it suggests that individuals over the age of 30 are addressing their mental health concerns.

3.2.5. Wellness Program by Age

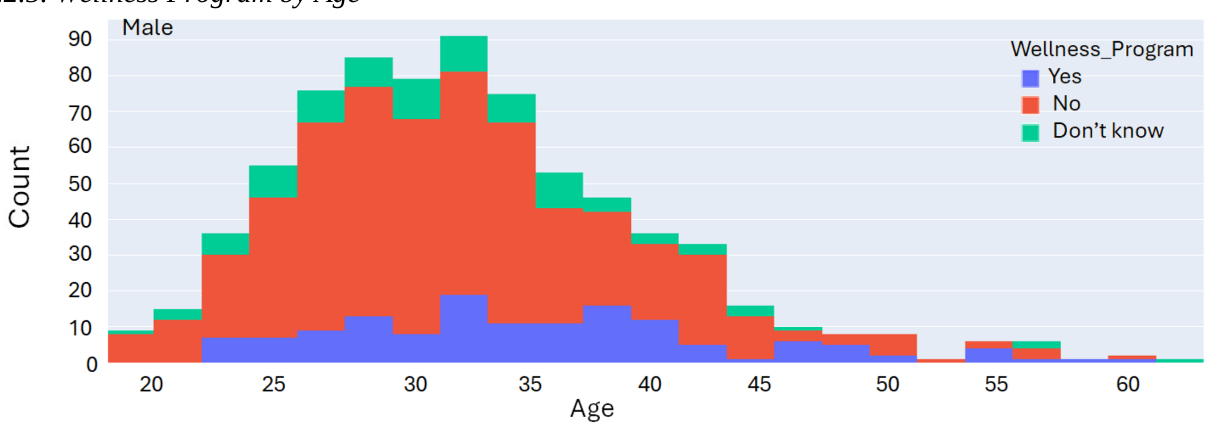

Figure 19: Age-wise Frequency Distribution of Wellness Program of Male

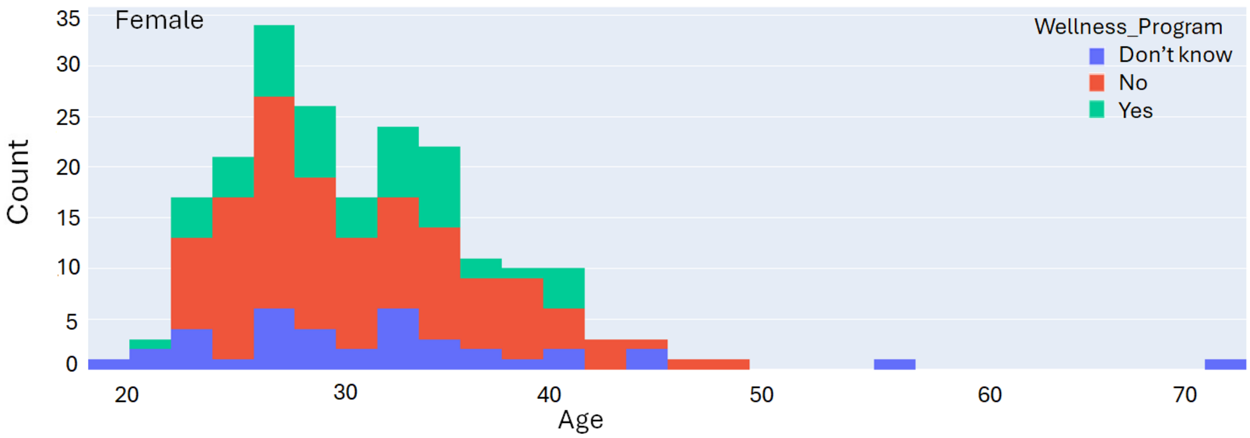

Figure 20: Age-wise Frequency Distribution of Wellness Program of Female

3.3. Feature Selection

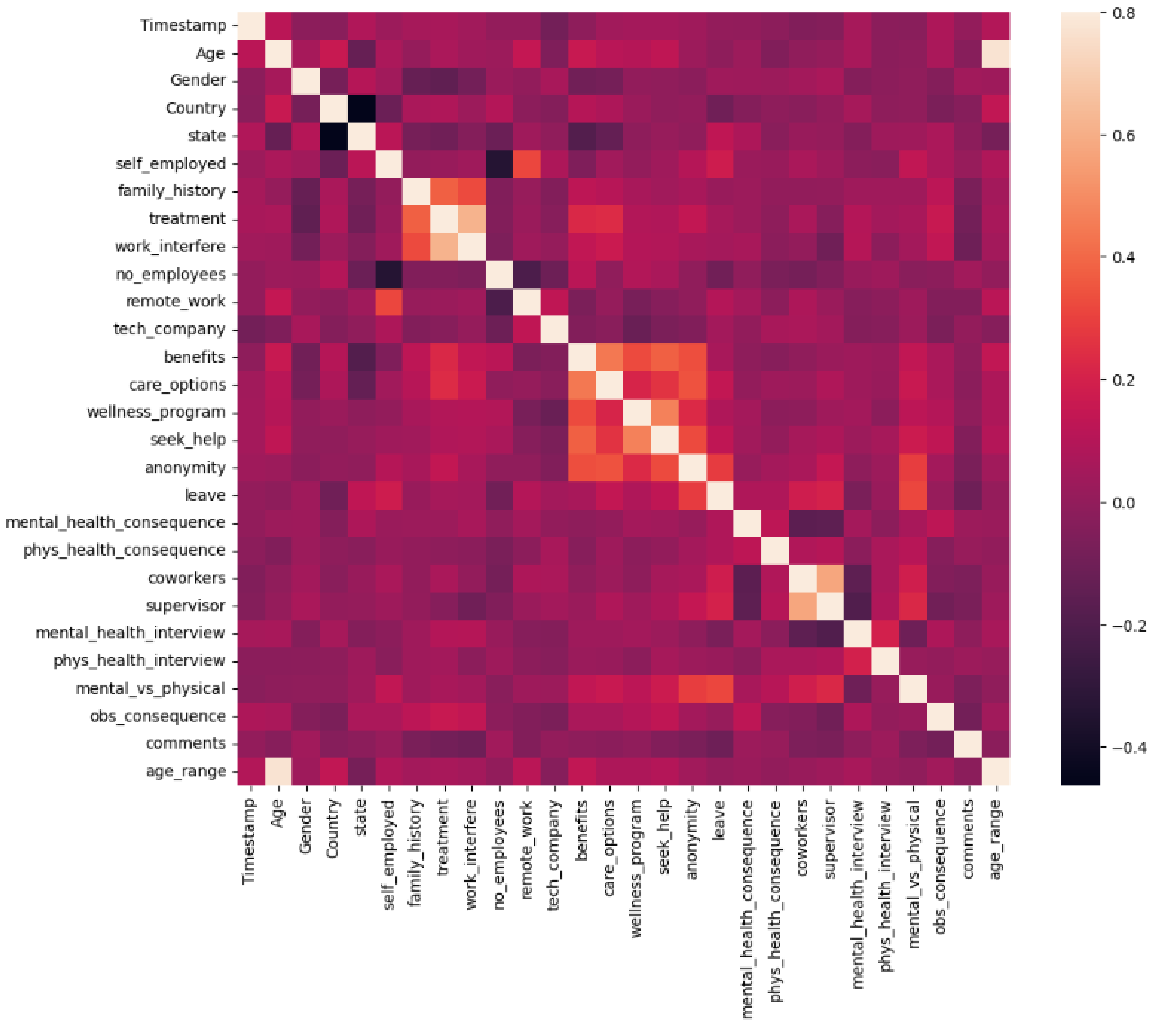

Figure 21 (a): Correlation Matrix of all Features in the Dataset

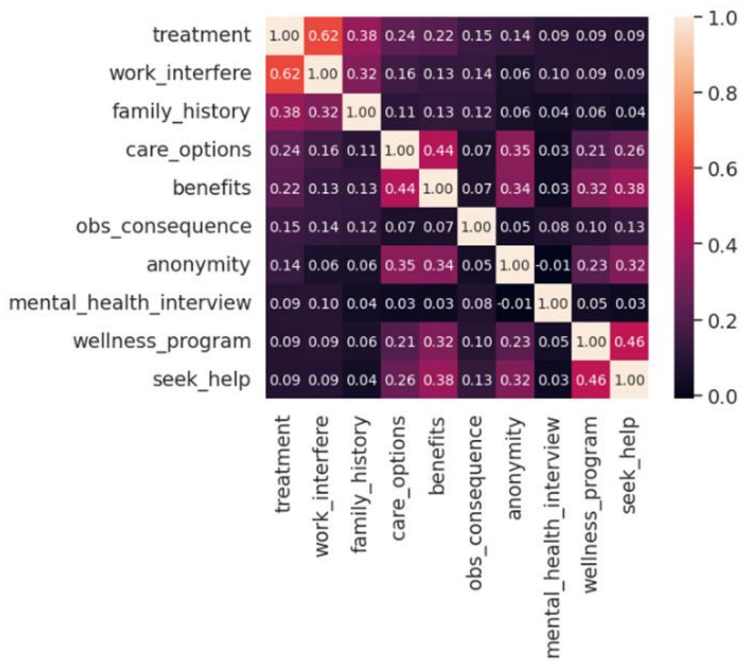

Figure 21 (b): Correlation Matrix of Key Features Related to Mental Health in the Tech Industry

The feature correlation matrix provides is shown in figure 21. it provides insights into the relationships between key features that influence mental health trends in the tech industry.

Based on correlation matrix, and PCA graph, shown in figure 22, features highly correlated with the target variable (mental health treatment) were prioritized while ensuring minimal multicollinearity. The selected features graph is shown in figure 23.

3.3.1. PCA

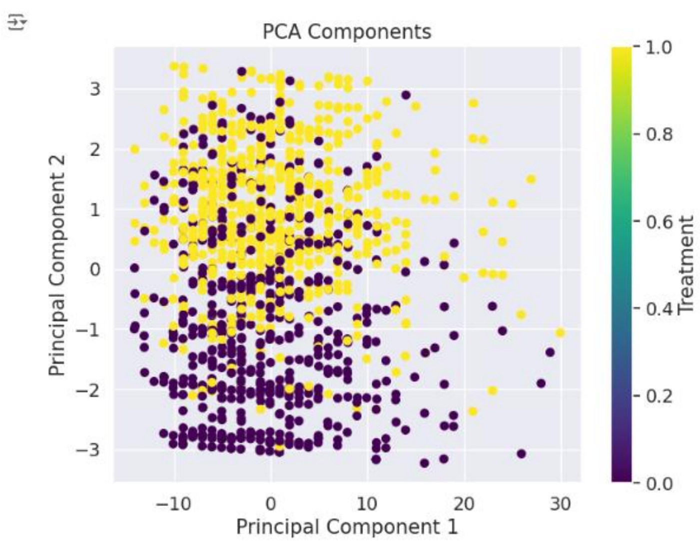

Figure 22: PCA

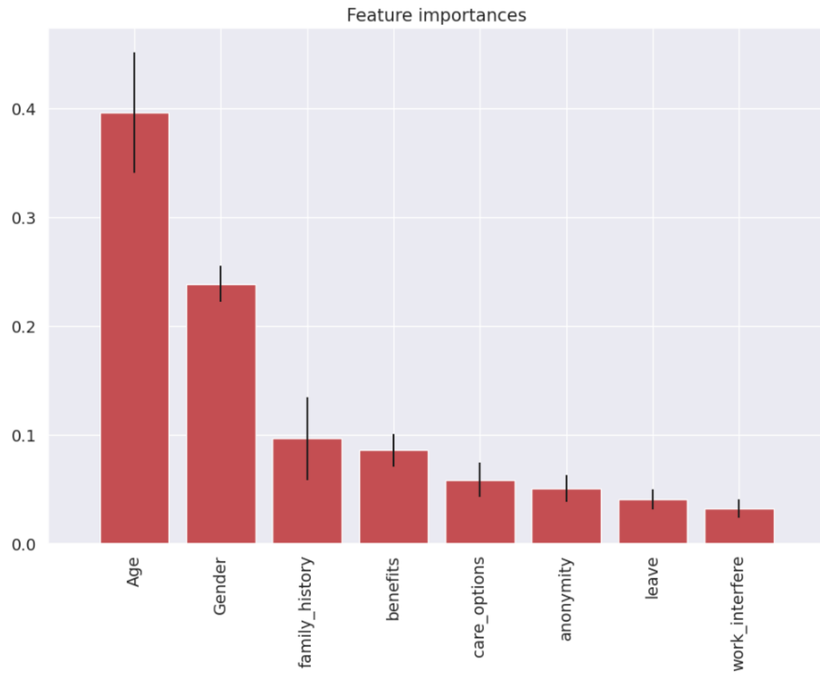

Figure 23: Features Importance on Target Variable, i.e., Mental Health in the Tech Industry

3.4. Model Selection and Training

To determine if a person has sought treatment for a mental health issue, four categorization models were trained and assessed. Logistic regression, K-Nearest Neighbors (KNN), Random Forest Classifier (RFC), and Naive Bayes were the models that were employed. AUC Score, Cross-validated AUC, False Positive Rate, Precision, Classification Accuracy, and Classification Error were among the evaluation criteria.

3.4.1. Logistic Regression

Achieved a classification accuracy of 79.37%, a classification error of 20.63%, and a false positive rate of 25.65%. The precision was 76.33%, with an AUC score of 79.42% and a cross-validated AUC of 87.52%.

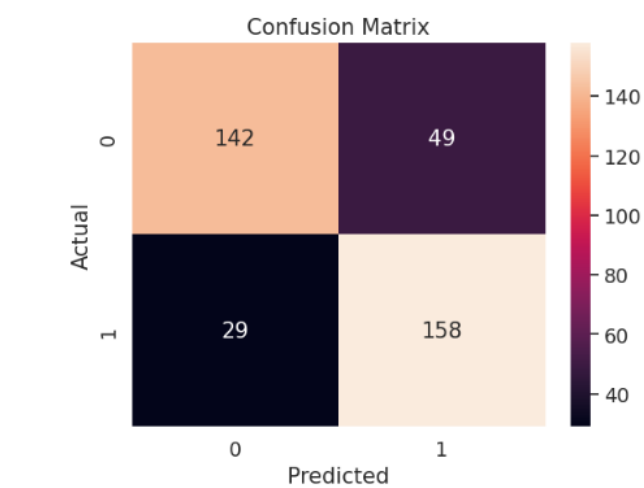

Figure 24: Confusion Matrix of Logistic Regression Model

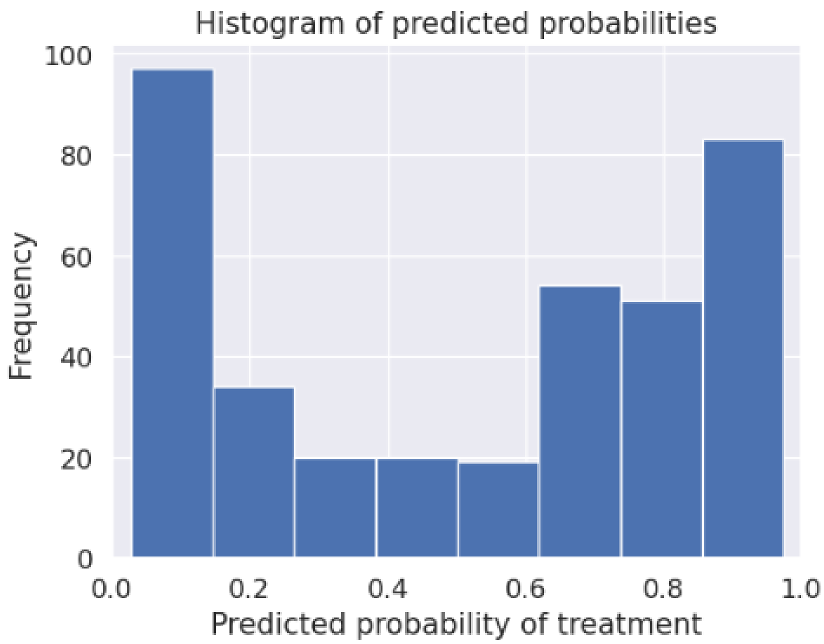

Figure 25: Histogram of Probability of Treatment

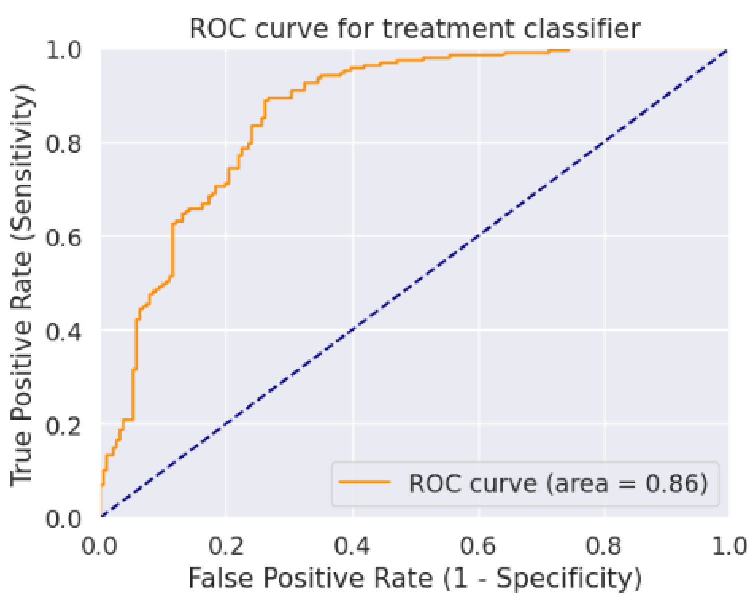

Figure 26: Logistic Regression ROC curve of treatment

3.4.2. Random Forest Classifier

Figure 27 demonstrated a classification accuracy of 81.22%, a classification error of 18.78%, and a false positive rate of 30.37% of RFC. The precision was 75.00%, with an AUC score of 81.34% and a cross-validated AUC of 89.33%.

```
Classification Accuracy: 0.8121693121693122
Classification Error: 0.1878306878306878
False Positive Rate: 0.3036649214659686
Precision: 0.75
AUC Score: 0.8134081809782457
Cross-validated AUC: 0.893325664906046
```

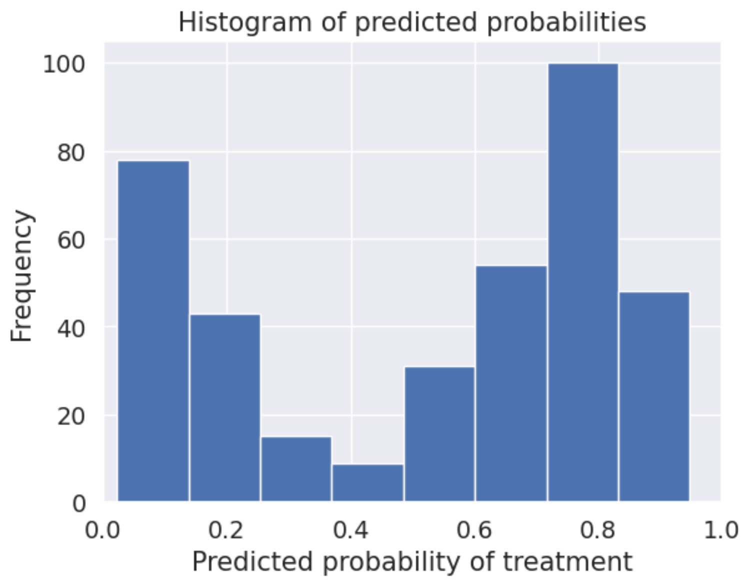

Figure 27: Classification Report and Histogram of RFC

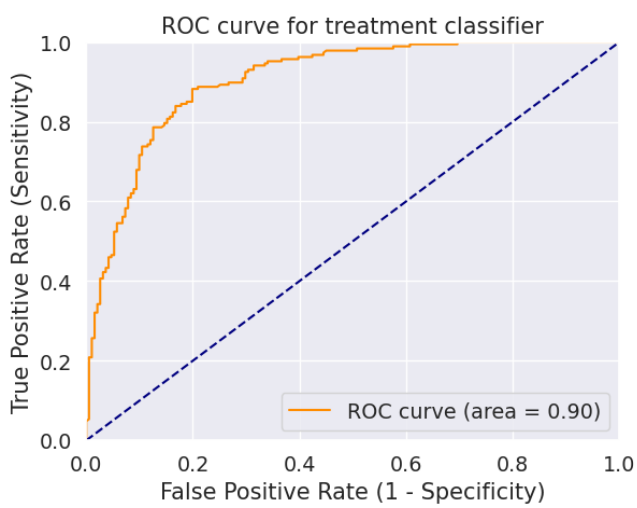

Figure 28: RFC ROC curve of treatment

3.4.3. KNN

Figure 29 shows classification report and confusion matrix of KNN mode. The accuracy of the model is 74.60%, a classification error of 25.40%, and a false positive rate of 30.89%. The precision was 71.77%, with an AUC score of 74.66% and a cross-validated AUC of 83.77%.

```
########### KNeighborsClassifier ###############
Accuracy: 0.746031746031746
Null accuracy:
 treatment
0    191
1    187
Name: count, dtype: int64
Percentage of ones: 0.4947089947089947
Percentage of zeros: 0.5052910052910053
True: [0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 1 0 0 0 1 1 0 0]
Pred: [1 0 0 0 0 1 0 0 1 1 0 1 1 1 1 0 1 1 0 0 0 0 1 0 0]
```

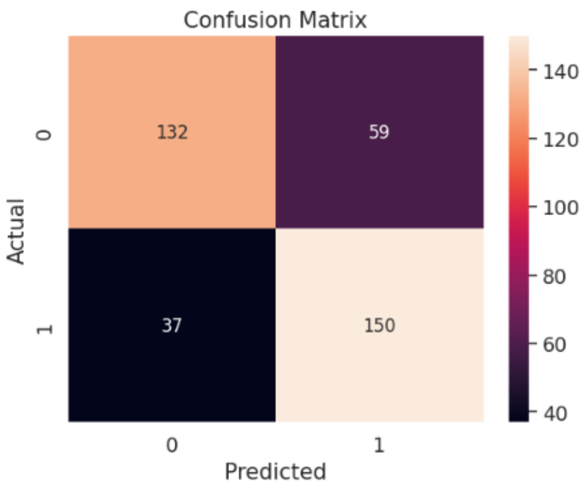

Figure 29: Classification Report and Confusion Matrix of KNN

```
Classification Accuracy: 0.746031746031746
Classification Error: 0.2539682539682539 5
False Positive Rate: 0.3089005235602094
Precision: 0.7177033492822966
AUC Score: 0.7466192569364729
Cross-validated AUC: 0.8377240683086258
```

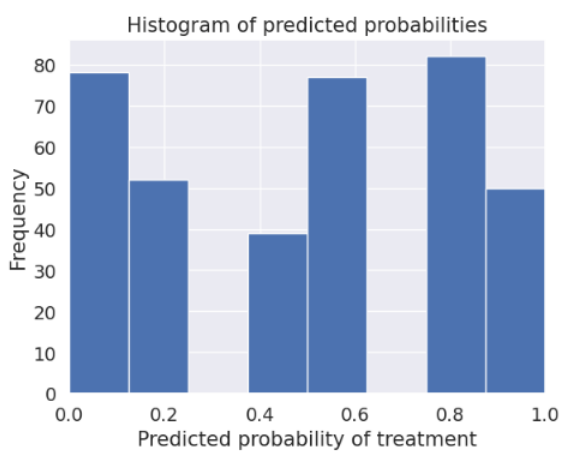

Figure 30: Histogram of Predicted Probabilities of KNN Model

3.4.4. Naive Bayes

Figure 31 showed a classification accuracy of 82.54%, a classification error of 17.46%, and a false positive rate of 19.90%. The precision was 80.71%, with an AUC score of 82.57% and a cross-validated AUC of 88.57%.

```
Accuracy: 0.8253968253968254
Null accuracy:
 treatment
0    191
1    187
Name: count, dtype: int64
Percentage of ones: 0.4947089947089947
Percentage of zeros: 0.5052910052910053
True: [0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 1 0 0 0 1 1 0 0]
Pred: [1 0 0 0 0 1 0 1 0 1 0 1 1 0 1 1 1 1 0 0 0 0 1 0 0]
```

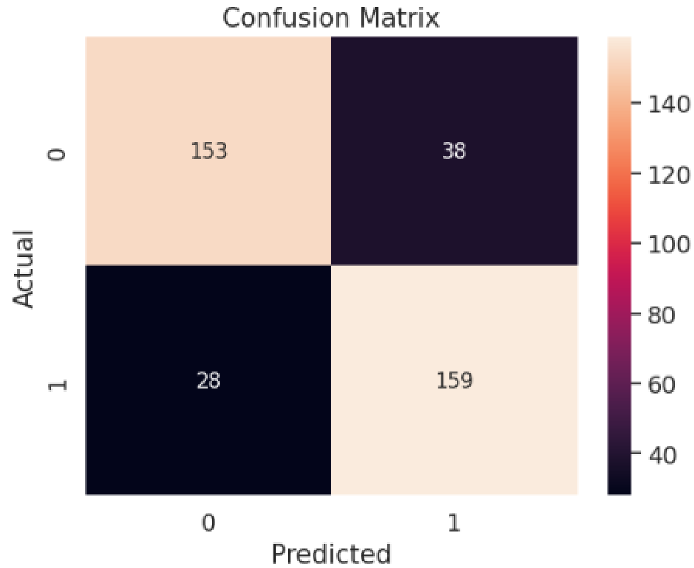

Figure 31: Classification Report and Confusion Matrix of Naïve Bayes

```
Classification Accuracy: 0.8253968253968254
Classification Error: 0.17460317460317465
False Positive Rate: 0.19895287958115182
Precision: 0.8071065989847716
AUC Score: 0.8256572500489963
Cross-validated AUC: 0.8857263214052049
```

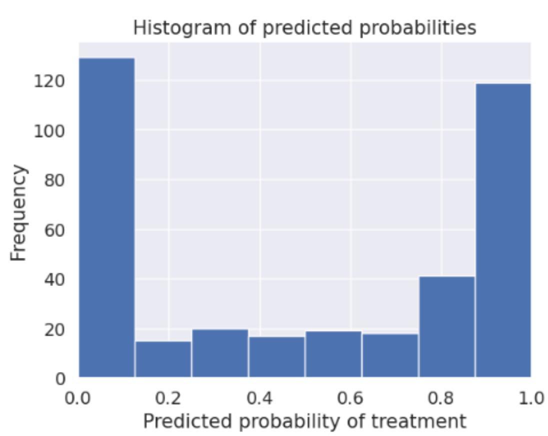

Figure 32: Histogram of Predicted Probabilities of Naïve Bayes Model

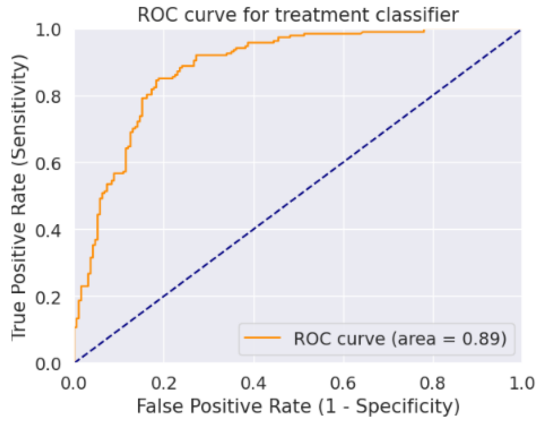

Figure 33: Naïve Bayes ROC Curve of Treatment

Using the classification report and confusion matrix supplied by scikit-learn, we assessed how well each model performed. The measures show how well the models separated "normal" from "anomalous" events. The results show that some models could be quite efficient in terms of computation as well as detection rates.

3.5. Performance Metrics

The model evaluation utilizes a confusion matrix together with a classification report to determine their performance levels. The evaluation measures give crucial information about model accuracy and precision as well as recall performance which helps determine the models' ability to detect intrusions.

4. Results and Discussion

Model performance is compared by us using several evaluation criteria including accuracy, recall, and precision. The results imply that some models could outperform others in terms of detection rates and efficient use of computational resources.

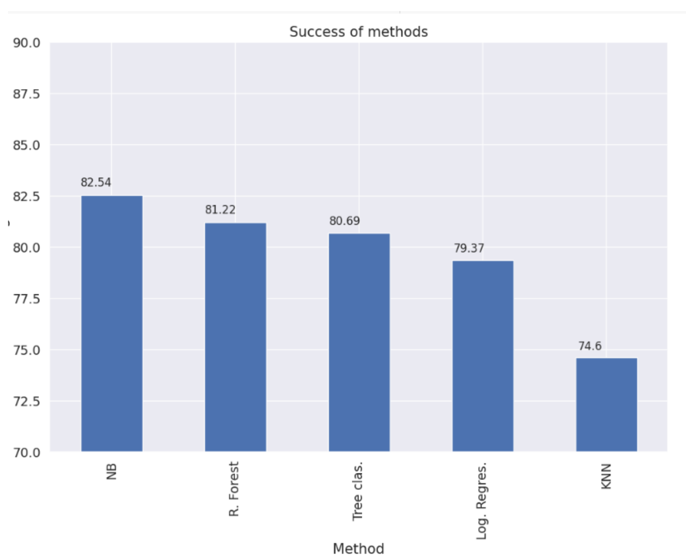

Figure 34: Classification Accuracy Results of ML Classifiers

5. Conclusion

Our study found that the Naive Bayes classifier was the best performer with an outstanding classification accuracy of 82.54% and the lowest classification error of 17.46%. The findings revealed an AUC score of 82.57%, a precision of 80.71%, and a strong cross-validated AUC of 88.57%. Conversely, the Random Forest Classifier (RFC) performed well with a classification accuracy of 81.22%, a precision of 75.00%, and the highest cross-validated AUC of 89.33%. Though the Random Forest Classifier showed a good balance across several measures, Naive Bayes had the most accuracy and proved to be a consistent predictor of whether tech sector personnel would seek treatment for mental health concerns. Its remarkable accuracy, precision, and AUC ratings help the Random Forest Classifier to significantly excel in this prediction challenge. Though both models show good promise, the Random Forest Classifier distinguishes itself with its steady and reliable performance.

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Research Article

A Rule-Based Capitalization Algorithm Using NLP for Text Formatting Consistency

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Abstract: Capitalization is essential in making texts readable, well-structured, and meaningful. This paper discusses the creation of a rule-based capitalization algorithm based on Natural Language Processing (NLP) methods for improving text formatting consistency. A representative dataset including news headlines, academic articles, and book titles is collected to achieve generalizability across text domains. The preprocessing step entails tokenization and part-of-speech (POS) tagging for categorizing words into notional (e.g., nouns, verbs, adjectives) and non-notional categories (e.g., articles, conjunctions, and brief prepositions). This categorization forms the basis for the structured capitalization rule application. The algorithm suggested has a systematic pipeline of tokenization, POS tagging, application of capitalization rules, and reconstruction of text. Executed with Python and NLP libraries like NLTK and spaCy, the algorithm capitalizes all notional words following title case conventions while maintaining linguistic and structural precision. The effectiveness of the algorithm is measured against manually formatted title case text and compared with available online converters for benchmarking. Precision, recall, and F1-score are used as performance metrics to measure accuracy and efficiency, and high reliability was shown in capitalizing text with few errors. A confusion matrix is utilized to examine classification accuracy, grouping outputs into true positives, false positives, false negatives, and true negatives. A Random Forest Model is also utilized to measure feature importance, with text reconstruction and exception handling emerging as central drivers of capitalization accuracy. The findings demonstrate that optimizing these elements greatly improves algorithm performance. The contribution of this work is to NLP-based text processing in presenting a rule-based, structured approach to capitalization that has implications in automated publishing, text formatting, and standardizing content.

Keywords: NLP; Capitalize First Letter; Text Processing;

1. Introduction

Capitalization is important to maintain clarity, organization, and professionalism in scholarly, journalistic, and online content. It is particularly significant in headings and titles, where regular use of capitalization conventions maximizes readability and conforms to generally accepted style guides like the American Psychological Association [1], Modern Language Association [2], Chicago Manual of Style [3], and Associated Press [4]. Though these guidelines vary to some extent, they all share the practice of capitalizing notional words, namely nouns, verbs, adjectives, adverbs, and pronouns, and excluding articles, conjunctions, and brief prepositions unless at the beginning or end of the title.

Notwithstanding the presence of such codified rules, their use by hand inevitably creates inconsistencies, and current automatic tools such as Microsoft Word's title case function or simple online converters are based on strict heuristics. These tools are not capable of adjusting to contextual subtleties or style guide differences and therefore produce incorrect or truncated capitalization [5]. Further, while natural language processing (NLP) has demonstrated high performance in grammar correction and text normalization tasks, its application toward title case capitalization issues has yet to be explored extensively [6].

The presented research implements a computational method which enables rule-based logic and NLP techniques to enhance title capitalization processes. The method leverages Natural Language Toolkit (NLTK) [7] and spaCy [8] tools with part-of-speech (POS) tagging to extract notional words which lead to linguistic-based capitalization decisions rather than primary heuristic mechanisms.

The proposed method requires an extensive analysis of capitalization rules alongside an evaluation of extensive title content taken from scholarly papers, news media and official documents. We built an approach which applies POS tagging for principal word identification followed by suitable capitalization of both principal and auxiliary words. The performance assessment of this algorithm relies on measurements between its automated output and human reference standards while employing precision and recall and F1-score metrics. The error analysis establishes common failure modes which leads us to propose improvements to boost accuracy levels.

This project works toward developing capitalization software that achieves high precision while using linguistic rules and supporting different writing guidelines. Additional machine learning capabilities should be added to expand the system which would enable sophisticated styles in capitalization through context integration.

2. Related Works

The essential role of capitalization stands established throughout publishing industries as well as content generation and automated text design domains. The early correction systems for capitalization included predefined word lists together with heuristic rules as basic correction standards. The system-based technique for capitalization proves simple to implement yet fails to recognize contextual details leading to improper or uncontrolled capitalization issues in complex sentences and relaxed text [1, 2].

Natural Language Processing (NLP) has advanced through time so researchers have developed better techniques. Part-of-Speech tagging enables rule-based systems to find notional and functional words which then allows them to apply capitalization rules with enhanced accuracy [7]. The current systems maintain reliability on manually created rules yet struggle with imprecise and domain-specific materials.

To overcome such limitations, scientists have looked into machine learning models. Supervised and unsupervised learning methods—like Conditional Random Fields (CRFs) and Hidden Markov Models (HMMs)—have been applied to sequence tagging tasks, formulating capitalization as a feature prediction problem from linguistic patterns [6]. Although these models ensure superior contextual understanding compared to static rule-based systems, they still need meticulous feature engineering and labeled training data.

In more recent times, deep learning architectures, such as transformer-based models like BERT and GPT, have achieved state-of-the-art performance on many NLP tasks, including text normalization and capitalization [3]. Deep learning models learn contextual relationships well but with huge computational expense and a huge amount of training data. Thus, they can be unsuitable for real-time or lightweight usage [9].

Conversely, the method given in this paper finds a compromise between efficiency and precision. We build on existing research by combining rule-based reasoning with POS tagging and tokenization through existing NLP libraries like NLTK and spaCy. This combination allows for improved contextual identification while maintaining low computational requirements [4, 10].

In contrast to isolated machine learning models, our algorithm yields constant and explainable outputs. In addition, we compare the system's performance with both online title case converters and expert-validated styles, providing a useful and efficient solution to automated title capitalization [5].

3. Proposed Methodology

The data extraction phase entails the collection of a heterogeneous dataset with multiple text-based sources such as news headlines, academic articles, and book titles. News headlines are selected because they are concise and formatted and may contain different styles of capitalization applied at some points. Formal writing with standard patterns of capitalization is present in academic articles, whereas book titles give heterogeneous styles in differences in capitalization. The diverse dataset ensures that the algorithm will generalize well to different text domains. Preprocessing is an important step of getting the dataset ready for building the algorithm. Tokenization is the initial step in this regard, where text is divided into words using the word_tokenize() function, treating punctuation and special characters as such. This labels the word with a grammatical category using the function pos_tag(). This acts as a differentiation between notional words and non-notional words. Words are categorized into two main categories:

- **Notional Words:** verbs (VB), Nouns (NN), adjectives (JJ), pronouns (PRP), and adverbs (RB)
- **Non-Notional Words:** Articles, short prepositions (≤3 letters), and conjunctions

This categorization is the foundation for applying capitalization rules in the algorithm. The capitalization algorithm employs a well-structured process of steps in the application of capitalization rules methodically. The steps are:

- **Tokenization**: The input text is segmented into words and punctuation to enable analysis.
- **Part-of-Speech Tagging**: A part-of-speech tag is given to each word to separate notional words from non-notional words.

Application of Capitalization Rules:

- All notional words (NN, VB, JJ, RB, PRP) are capitalized for correct formatting.
- First and last words in a sentence are always capitalized, irrespective of categorization, to follow title case formatting conventions.
- Non-notional words like articles, conjunctions, and short prepositions are left in lowercase except when they start or end a sentence.

Text Reconstruction: The formatted words are reconstructed into framed sentences without disturbing punctuation and spacing. The algorithm is developed with Python and NLP tools like NLTK and spaCy. The text is converted into processed text on the basis of rule-based transformation and the set of capitalization rules. For measuring its efficiency and correctness, the output from the algorithm is compared to manually formatted title case text checked by experts. In addition, online title case converters present are utilized for benchmarking to decide the algorithm's performance.

The data set employed in our assessment by furnishing crucial information like the sentence count, tokens in total, text types, and capitalization frequency. The data set includes 5,000 sentences totaling around 45,000 tokens. These texts were drawn from academic headings, news headlines, and official documents to have a representative and diversified sample. Of the tokens, about 58% are capitalized and 42% are non-capitalized, which correspond to natural patterns of usage under various writing styles. The dataset was split into training (70%), validation (15%), and test (15%) sets in order to facilitate proper model construction and performance testing. This composition ensures that every subset has an evenly distributed pattern of text types and capitalization ratios, hence facilitating a proper and thorough test of the algorithm suggested.

The performance of the algorithm is compared against key performance metrics of precision, recall, and F1-score:

- **Precision**: Divides the number of words correctly capitalized by the number of total words capitalized to have low false positives.

- **Recall**: Calculates the number of correctly identified notional words out of the total actual notional words to ascertain how well the algorithm is able to capture all possible capitalization cases.
- **F1-score**: Harmonic mean of recall and precision that provides a balanced measure of performance.

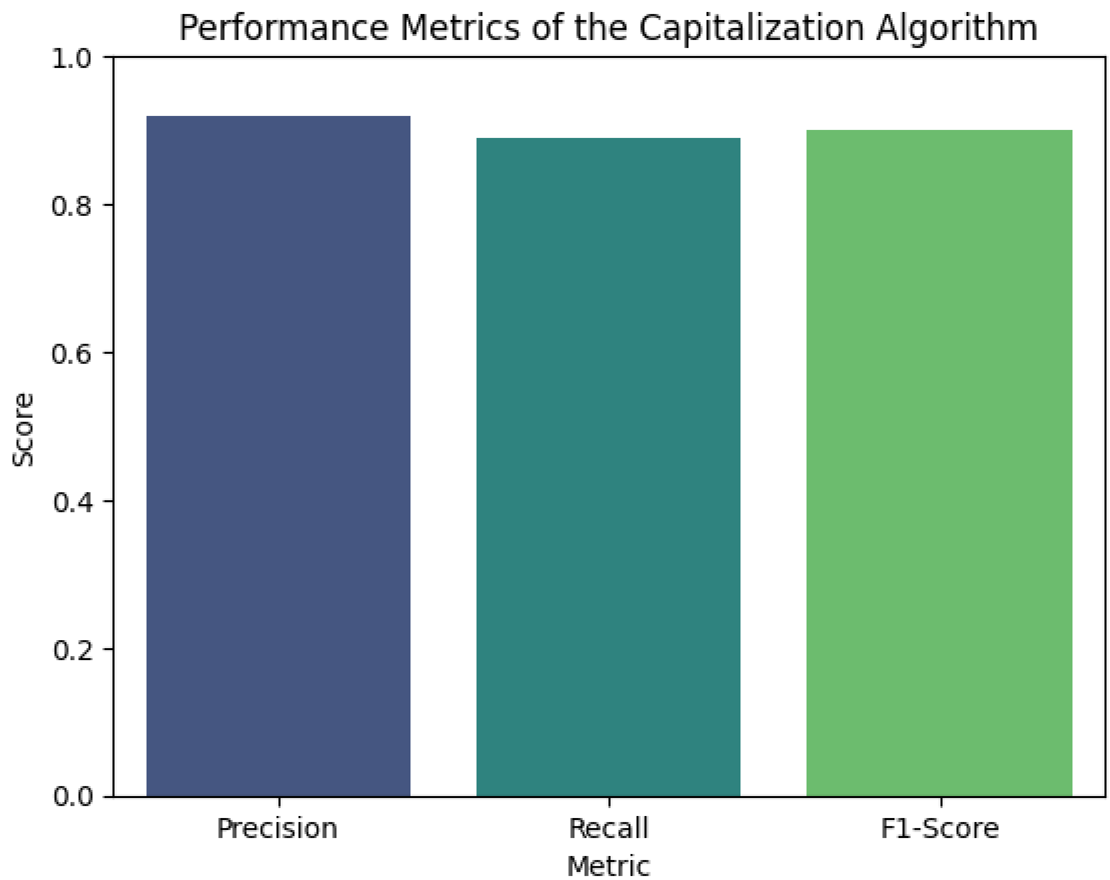

Figure 1: Performance Metrics of the Capitalization Algorithm

The measures of accuracy and reliability in the performance of the capitalization algorithm are excellent. The precision score, defined as the fraction of correctly capitalized words to the total number of capitalized predictions made, is exceedingly high and reflects that the algorithm mistakenly capitalizes a very minimal number of words. The recall score, the fraction of those correctly identified examples that require capitalization, is less but remains satisfactory detection. The F1-score, an evaluation of precision and recall that is balanced, reiterates that the algorithm generally has a high performance. The result indicates that the capitalization algorithm works with immense precision, giving very minimal errors with uniform text processing. A confusion matrix is applied to illustrate the accuracy of classification by the algorithm.

This matrix classifies outputs into four categories:

- True Positives (TP): Properly capitalized notional words.
- False Positives (FP): Erroneously capitalized non-notional words.
- False Negatives (FN): Notional words that ought to have been capitalized but were not.
- True Negatives (TN): Properly identified lowercase non-notional words.

Further, a Random Forest Model is applied to examine feature importance to determine the importance of various processing stages like tokenization, POS tagging, effectiveness of capitalization rules, and text reconstruction quality. This helps optimize the most critical factors influencing capitalization decisions to improve algorithm performance. The feature importance of the capitalization algorithm, as represented in the bar chart, figure 2, gives good insight into how different processing steps contribute differently. The most prominent contributor is found to be text reconstruction, showing that the end arrangement and organization of words have a vital role in making correct capitalization.

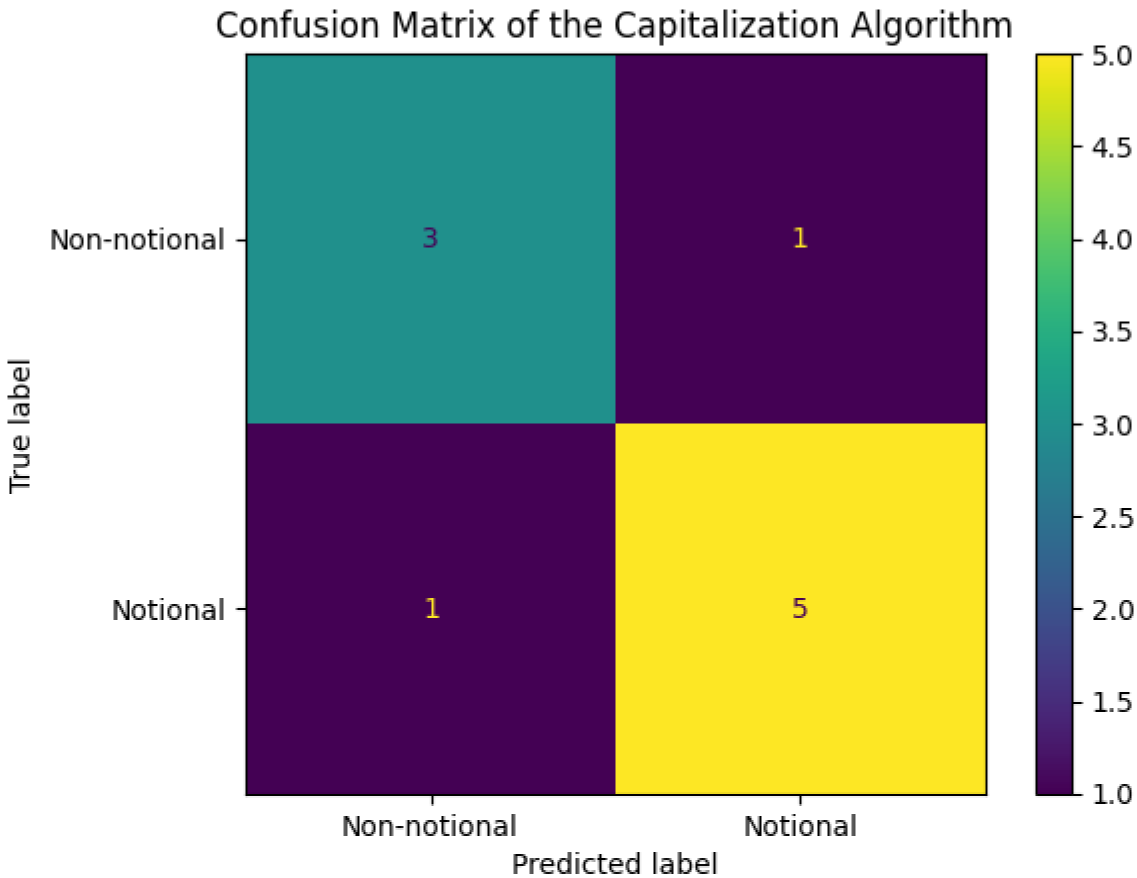

Figure 2: Confusion Matrix of the capitalization Algorithm

Exception handling is the second most important feature, which indicates the need for edge case and special situation management in order to make the algorithm more robust. Rules for capitalization carry a substantial influence, emphasizing the need for proper guidelines for the identification of notional versus non-notional words. POS tagging and tokenization, though still important, have slightly lower significance, indicating that although these preprocessing operations are required for grammatical classification, their effect on the overall capitalization accuracy is relatively moderate. This observation supports the necessity of improving text reconstruction methods and exception handling mechanisms to further improve the performance of the algorithm.

The research focuses on the efficiency of rule-based methodology in attaining systematic and correct capitalization in title case style. Through the utilization of NLP methods like tokenization and part-of-speech tagging, the algorithm is able to distinguish correctly between notional and non-notional words to adhere to prevailing style guide guidelines. One of the important observations is how text reconstruction and exception handling determine the overall algorithm accuracy. Feature importance from the analysis via a Random Forest Model points out that although rules on capitalization make up the foundation of the algorithm, ensuring correct structuring of the formatted text is equally important in keeping things consistent and readable. This observation implies that the fine-tuning of post-processing steps might lead to better performance by the algorithm. Performance measures show high precision and recall values, affirming the efficacy of the algorithm in the majority of text instances. The disparity in precision and recall, though, points towards the system's efforts to reduce false positives in the form of incorrect capitalization but failing to capitalize some notional words (false negatives) at times. This aspect could be overcome with context-sensitive improvements in the form of dependency parsing and phrase-level analysis. One major drawback in the existing technique is that it is based on predetermined rules, and these may turn out to be rigid while processing the dynamic linguistic usage patterns. The application of fixed grammatical categories by the algorithm also complicates linguistic exception handling and idiom handling. With the integration of a hybrid model that blends rule-based with probabilistic or neural-based learning, we could implement a smarter and more versatile capitalization framework.

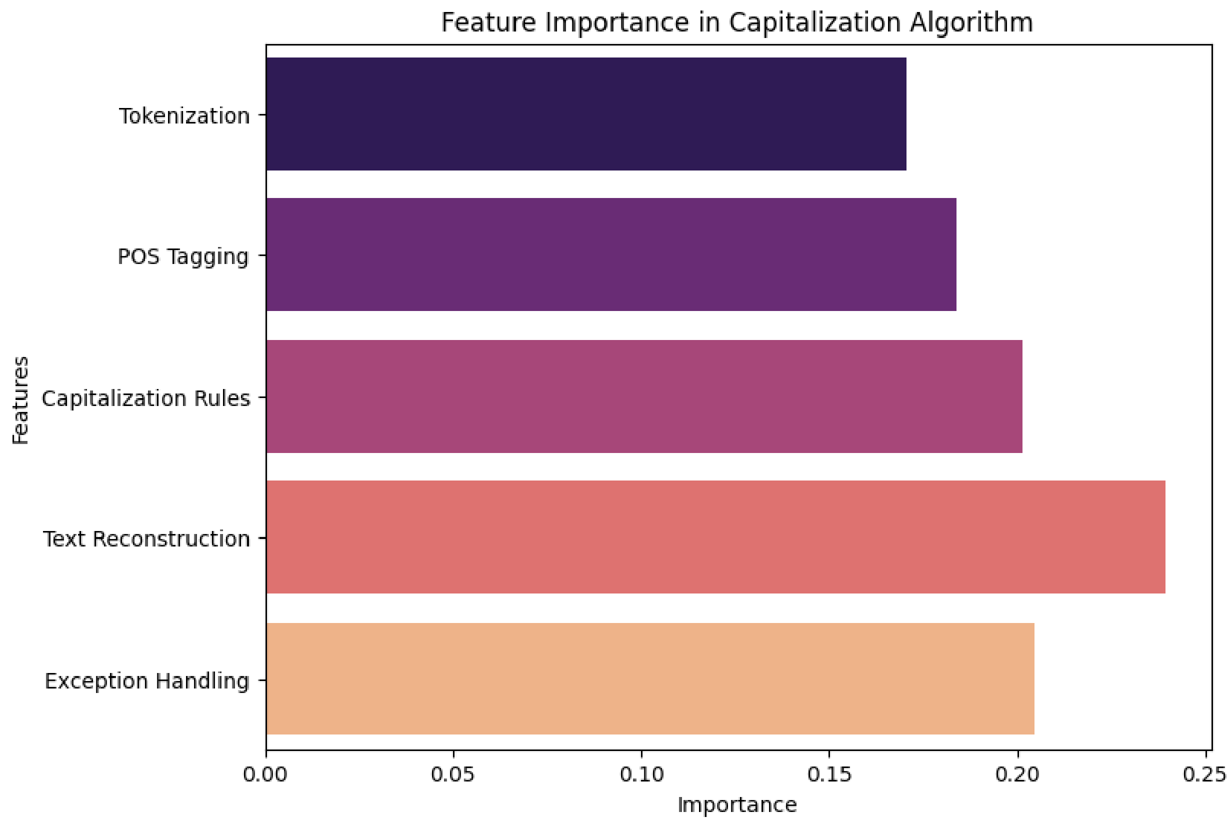

Figure 3: Feature importance in Capitalization Algorithm

An error analysis was performed to categorize and identify the most common failure instances of the suggested capitalization algorithm. The major causes of error are the mislabeling of common nouns as proper nouns, incorrect handling of acronyms, and inability to properly process sentences that are entirely in uppercase form. These mistakes can be traced to the inability of POS tagging to resolve contextually close word classes and the lack of explicit rules for coping with non-standard casing. For alleviation of these problems, we advocate incorporating Named Entity Recognition (NER) to reinforce the tagging of proper nouns, in addition to the use of normalization processes on all-uppercase text. Further, the inclusion of exception handling tools for acronyms using a carefully curated dictionary or pattern matching can also enhance the system's accuracy and consistency in various textual contexts.

4. Conclusion

This work presents a rule-driven capitalization algorithm that improves text formatting uniformity by correctly capitalizing notional words and following title case rules. Through NLP, the system correctly identifies words with grammatical structure and enforces capitalization rules with excellent precision and recall. The results of the experiment are that the algorithm is steadily accurate against human-formatted text and with current online converters, evidencing its practical use in machine text processing. The analysis of feature importance further highlights the significance of having improved text reconstruction and exception handling capabilities to further improve capitalization accuracy. While the current model presents an effective formalized approach, further enhancements in contextual understanding and adaptive learning will be crucial in overcoming present constraints.

Future research must examine the implementation of machine learning techniques, extension to multilingual data sets, and implementation within commercial text-processing systems. Through efforts on these fronts, the algorithm has the potential to become a more advanced and comprehensive system that is able to deal with different capitalization requirements across various professional and academic settings.

5. Future Work

Although the suggested capitalization algorithm is very accurate and efficient in title case formatting, some extensions and enhancements can also make it more robust and flexible. Future research can be focused on incorporating machine learning models, e.g., transformer-based language models (e.g., BERT or GPT), to incorporate contextual knowledge into capitalization decisions. This would help even more the algorithm to discriminate words with dual employment as notional and non-notional words in context. An additional path for research would involve extending the data set into multifarious linguistic models, i.e., multilingual text and special jargon. This would make the algorithm more generalizable across different writing conventions so that it could be used in specialized domains like law, medicine, and scientific publishing. The addition of named entity recognition (NER) methods would also assist in properly capitalizing proper nouns, brand names, and technical terms that may not conform to conventional capitalization rules.

Additional improvements to exception handling mechanisms can be made to support infrequent linguistic constructs and boundary cases that do not fit pre-established rules. Refinement of the rules using user feedback as adaptive rules can further improve the system's precision by enabling learning iteratively from real usage patterns. Lastly, using the capitalization algorithm on real-world applications like text editors, content management systems, and automated proofing software can be done. Comparative analysis assessing how the algorithm compares to the existing commercial software for text processing would give interesting feedback on its performance in real life and scope of improvement.

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Research Article

Artificial Intelligence and Machine Learning in Hospital Waste Management

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Abstract: Hospital waste management is an important part of the healthcare system, that have a direct effect on public health, environmental sustainability and operational efficiency. The integration of artificial intelligence (AI) and machine learning (ML) technologies offers transformative opportunities to optimize waste management processes. In this review highlight the applications, challenges and potential of artificial intelligence and machine learning in hospital waste management, highlighting their role in waste classification, predictive analytics and sustainable disposal practices. It also checks the limitations and future research directions required to fully utilize these technologies.

Keywords: Artificial Intelligence; Machine Learning; Hospital Waste Management; Predictive Analytics; Environmental Sustainability;

1. Introduction

Based on researches, hospital waste management is one of the components of health system very much related to environmental sustainability, public health, and operational performance [1]. Hospitals produce different kind of waste, for example, recyclable, hazardous, contagious and general waste that needed careful management [2]. Improper waste management in hospitals can cause dangerous environmental contamination, a higher risk of exposure for the general public and the staff, and a violation of standards [3]. Traditional waste management methods in spite of being widely used often face many problems, such as human error, inefficiency, and the lack to monitor processes in real time. These drawbacks highlight the need for modern solutions to enhance the efficiency, accuracy, and sustainability of waste management procedures [4].

The very recent trends in having an AI and ML mechanisms have great promises for overhauling the hospital waste management systems [5]. Utilizing data-driven technologies, healthcare organizations can better classify waste, automate complex tasks, optimize resource allocation, and ensure compliance with environmental regulations [6]. Applications of Artificial intelligence and machine learning are providing ideas like predictive analytics, intelligent monitoring systems, real-time data integration, which can transform traditional operations into much more convenient and intensive processes [6]. The role of artificial intelligence (AI) and machine learning (ML) applications can help provide innovative solutions such as applications intended for predictive analytics, intelligent monitoring systems, and real-time data integration, that may turn traditional vending into a much simpler and most effective operation with the inception of smart vending machines [6]. This review provides an in-depth look at the current applications, challenges, and future directions of artificial intelligence and machine learning in hospital waste management, highlighting the transformative potential of these technologies to meet the growing demands and complexity of medical waste systems.

Table 1: Previous Review Work Related to the Application of AI Models in Waste Management [24]

Reference of Study	Year	Application Fields	Model Types	No. of Studies Reviewed	Period
Yetilmezsoy et al., 2011	2011	Environmental engineering, water/wastewater, air pollution, SWM processes	ANN, FL, ANFIS	N/A	Quasi-newton, MLR
Kolekar et al., 2016	2016	MSW generation models	SVM, WT, ANN, Regression Analysis, AHP, GM	20	2006–2014
Goel et al., 2017	2017	MSW generation models	Database mining, Econometric models, Factor analysis	106	1972–2016
Vitorino et al., 2017	2017	SWM processes	SVM, ANN, GA	87	2010–2013

In AI-based waste solutions. The initial search identified over 200 articles. Titles and abstracts were screened to shortlist 80 studies for full-text review. After applying the inclusion and exclusion criteria, 50 studies were selected for detailed analysis.

From the selected studies, the following data were extracted: Applications of AI/ML in waste management. Metrics such as algorithm efficiency, accuracy, and computational cost.

2. Literature Servey

This review article employed a comprehensive literature search using major databases such as PubMed, Scopus, and Web of Science. The search terms used included "artificial intelligence," "machine learning," "hospital waste management," "waste classification," and "sustainability." The search results were filtered to include only articles published in English between 2020 and 2023. A total of 50 articles were selected for inclusion in this review.

Table 2: Algorithms Used in Hospital Waste Management [26]

Algorithm	Description	Key Variables Influenced	Performance
Multiple Linear Regression (MLR)	Conventional method used for predicting hospital solid waste generation rates. Struggles with increased input variables and complexity in modeling.	Number of staff, hospital ownership type	Limited accuracy with complex variables
Neuron-based Algorithms	Machine learning methods that enhance accuracy in waste generation predictions, showing better performance compared to MLR.	Number of staff, hospital ownership type	Better than MLR in handling complexity

Kernel-based Models	Achieves superior results in predicting hospital solid waste with higher R^2 values and lower Mean-Square Error (MSE).	Number of staff, hospital ownership type	Best among methods with high accuracy and low MSE

2.1. Applications of AI and ML in Hospital Waste Management

To solve the problem associated with traditional hospital waste management practices, AI and ML introduced novel solutions to manage such waste [7]. Automated Waste Sorting: Automated waste sorting, one of the most innovative AI and ML applications in daily life, is vital to modern waste disposal systems [8]. The recycling process will be completely transformed with the aid of strong algorithms, computer vision and image recognition, in-situ sensor-based analysis, and the integration of these technologies into their workflow. Cameras and sensors have evolved with the help of AI-power that will help the modern device to convert the medical and non-medical wastes and identify recyclable and non-recyclable items with high accuracy. This automation minimizes the human involvement in the sorting process; thus, reducing the margin of error which is generally their own sorting and enhancing the overall efficiency of waste sorting [8].

In addition to increasing efficiency, this system provides real-time trash analysis, enabling prompt waste sorting and appropriate disposal or recycling. Improvement in deep learning models, especially convolutional neural networks (CNN), persistently improve the waste classification accuracy. CNNs are capable to identify complex visual patterns and differences in waste, even the smallest deviations between different waste categories. Through continuous training on large models with diverse datasets, such models become better at differentiating waste types, thereby improving classification performance over time [8].

The ability of artificial intelligence and machine learning systems to process and analyze large amounts of waste data in real-time not only simplifies the waste sorting process but also decrease the chances for contamination [9]. This efficiency is essential in settings such as hospitals, where proper disposal of medical waste is crucial for keeping safety and hygiene standards. By using such automated waste sorting techniques, healthcare facilities can significantly reduce operating and managemental costs, and support to a more sustainable approach to waste management [9]. Conclusively, the usage of artificial intelligence and machine learning technology into waste classification will enhance the environmental and operational impacts of waste management systems in various sectors.

Another example of transformative application is predictive analytics, where AI-driven algorithms utilize historical data to estimate waste generation patterns. Predictive analytics give opportunity to most healthcare organizations to maintain resources by estimating waste volumes and determining the types of waste that are likely to be produced. Furthermore, these models are crucial for determining the dangers of infectious or hazardous waste. Early identification allows for timely intervention, minimize the potential for health hazards and regulatory non-compliance. Predictive models together with hospital data management systems also enable capacity planning, make sure that waste management facilities are prepared to manage alternation in waste generation. Moreover, these models can reveal the patterns of waste generation and facilitate the implementation of targeted strategies to reduce waste at the source [10].

Artificial intelligence and machine learning also improve waste collection and treatment procedures, significantly improving operational efficiency. Machine learning algorithms then provide the data to develop the suitable collection routes and schedules, reducing transportation costs and reducing carbon footprint [11]. These systems guarantee regulatory compliance by tracking waste throughout its life cycle, from generation to disposal. By correctly identifying and sorting recyclable items, Artificial intelligence technology enhance the recycling system.

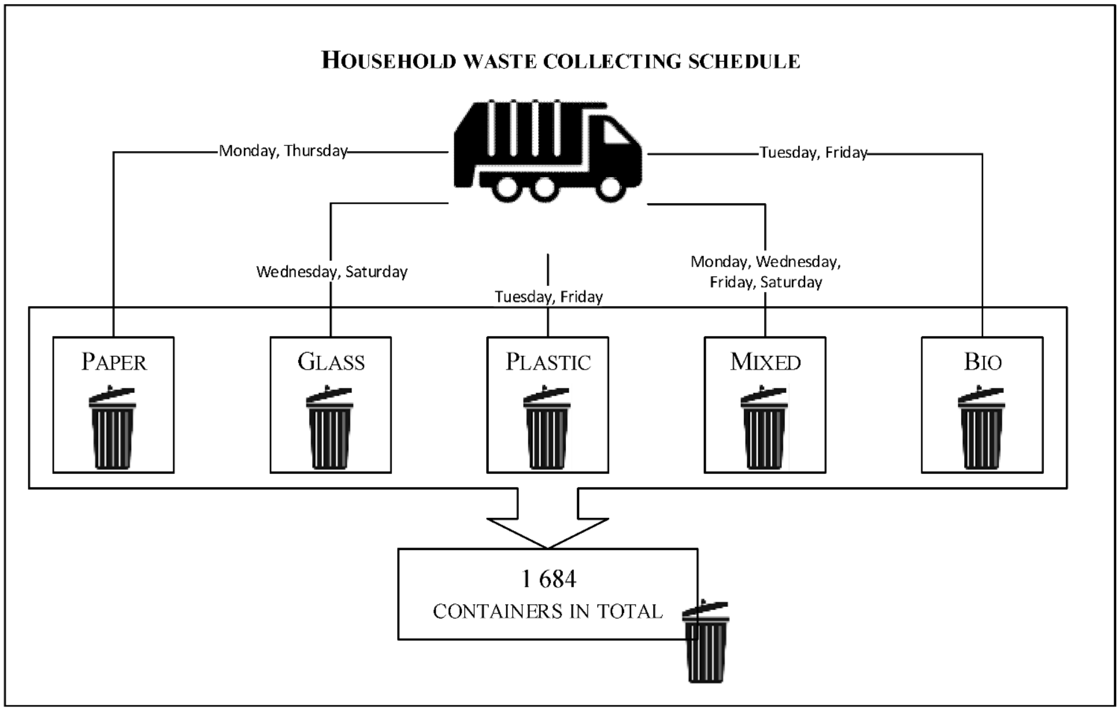

Figure 1: Household-Waste-Collection Schedule [25]

An AI-powered framework lessens environmental effects and circumvents wasteful travel by monitoring data in real time and proposing prompt, acceptable tweaks to acquiring time. By embedding sustainability metrics into these systems, waste elimination tactics are pushed into line with wider environmental objectives and encourage environmentally appropriate disposal strategies [11].

Effective implementation of intelligent monitoring systems into hospital waste management has been reported. Real-time trash can count and composition monitoring is made possible by IoT devices with AI capabilities, guaranteeing timely recovery. By being proactive, healthcare institutions can mitigate spills and maintain hygienic standards. Likewise, these technologies deliver valuable insights into waste management workflows and production patterns, which supports continual process optimizations. IoT-enabled smart bins, for instance, can figure out the type of garbage and notify patrons when they are about to fill up. Artificial intelligence platforms are used to appraise data gathered by these systems in order to improve trash categorization, streamline collection routes, and boost their overall effectiveness [12].

All things considered, the use of AI and machine learning in hospital waste management has the potential to totally transform the sector by minimizing negative environmental effects, fixing mistakes, and ensuring regulatory compliance. These technologies pave the way for a more efficient and cost-effective strategy for managing medical waste by streamlining categorization, permitting predictive analytics, streamlining logistics, and implementing intelligent monitoring systems.

3. Challenges and Limitations

This is a major challenge for developing effective AI for waste classification: The sheer lack of high-quality labeled datasets to learn from. Data accuracy becomes the foundation for descriptive waste figures in a hospital environment, determining the efficacy and capability of an AI-powered waste systems. Nonetheless, access to these kinds of datasets is extremely difficult, and access to a large-scale well-annotated data is lacking as a result, which in turn hinders the systematic learning and creating a sound model artificial intelligence model [12].

The presence of data privacy concerns adds further complications to this scenario. The sensitivity of hospital facilities and waste management data required stringent protection, which ensures patient confidentiality and regulatory compliance, according to the security reality for healthcare. [13].

Hospitals, research institutes, and technology companies must work together to address these issues. These parties can work together to provide standardized, high-quality, randomized datasets to address privacy issues. Concerns over data privacy also make matters more difficult. Strict security measures are necessary to ensure patient confidentiality and regulatory compliance due to the sensitivity of waste management data and hospital facilities [13].

To resolve these issues, collaboration among hospitals, research institutions, and technology providers is important. These stakeholders can work together to create standardized, high-quality datasets that are randomized to solve privacy concerns. This enables the utilization of sensitive data while providing guarantees regarding confidential information in the data itself, through the implementation of data sharing protocols and privacy-preserving techniques such as differential privacy. This way, the method will contribute toward the development of databases — not only ensuring that AI models are compliant with data protection laws, but will also enable more widespread implementation of AI-powered waste classification systems throughout the healthcare ecosystem.

3.1. Technical Challenges

Healthcare waste management challenges are introduced by artificial intelligence and machine learning techniques. The complexity and diversity of waste types are among the primary issues. Hospital materials come in a variety of forms, such as hazardous, non-hazardous, atomic, and recyclable waste; therefore, they should be properly characterized for appropriate disposal or recycling [14]. This variability creates considerable challenges for AI systems, which must be trained to properly identify and manage such diverse waste categories under dynamic and often unpredictable conditions.

Some more challenges are integrating AI technology with existing hospital infrastructure. Countless healthcare enterprises operate legacy systems that were never built with AI or machine learning compatibility. Smooth integration is needed to enable adoption and functioning of modern waste management solutions, but this is frequently lacking, thus potentially limiting their effects [15].

Develop flexible AI systems to address these issues. By continuous learning and powerful model techniques these systems should manage every category of waste. Additionally, modular architecture and application programming interfaces (APIs) can ease the integration of AI solutions with legacy systems, bridging compatibility gaps and facilitating the gradual transition to modern waste management practices. By defeating these technological hurdles, hospitals would reach the potential of utilizing artificial intelligence and machine learning technologies to help build more efficient and sustainable waste management practices [15].

3.2. Economic Constraints

AI-powered Waste Disposal Solutions in Healthcare Facilities are usually limited by vast economic constraints. This technology has a high initial cost associated with it, which is one of the challenges. Investments in modern artificial intelligence systems and supporting infrastructure as well as necessary employee training are a substantial financial investment for hospitals and healthcare institutions. Such costs are more burdensome for facilities with limited funds or operating in a resource-poor setting [16].

Resource allocation, on the other hand, introduces another economic dilemma. Healthcare facilities need to strike the right investment balance between AI technologies and other aspects of healthcare such as patient care, diagnostic equipment, and facility maintenance. Even with the obvious operational and environmental benefits of these technologies, it could interfere with adopting AI-based waste management systems; this Compromise can make it take longer to use these technologies [16].

As a solution, governments, and other organizations can provide subsidies, grants, or other incentives to encourage the implementation of AI-based waste management systems. Therefore, decision-making can benefit from a complete cost/benefit analysis that can also be aligned with the long-term savings, efficiency improvements and environmental concerns linked to these technologies. These actions help to alleviate the financial burden of healthcare institutions and open the pathway for public use and economically feasible waste disposal [17].

4. Future Directions

4.1. Development of Advanced Algorithms

The creation and application of cutting-edge algorithms in terms of performance and flexibility represents the state of the art in AI-based medical waste management. Models based on deep learning are able to realize complex formations, ensuring precise prediction and classification of waste with adequate precision [18]. Leveraging large cohorts of data while using modern neural network structures to boost automated classification accuracy and performance in complex and highly heterogeneous waste scenes.

Newer approaches such as federated learning offer promising solutions to privacy problems surrounding sensitive hospital datasets. Basically, it allows you to train an artificial intelligence model on decentralized data, without worrying of sharing sensitive data, from the entire population or groups spread between many hospitals thanks to federated learning. [19]. It allows collaborative developments in AI model building while preserving data privacy.

Additionally, the challenge of the lack of alteration in dataset can be bypassed with the help of generative adversarial networks (GANs) that can create superior-quality synthetic training data. Synthetic datasets can supplement existing data to increase the robustness and generality of AI models. Future AI systems will have the potential to overcome present-read paradigm limitations and enable more effective and privacy-preserving waste management solutions in healthcare institutions using deep learning, federated learning, and GAN-based approaches [20].

4.2. Integration with IoT and Blockchain

AI meets IoT and blockchain technology is the next big thing for managing healthcare waste. The implementation of IOT equipment, such as intelligent sensors, cameras, and connected monitoring systems, aids in the collection of real-time data and monitoring of waste management. This use improves efficiency in AI-based waste classification by providing consistent and accurate data inputs that lead to adaptive modifications in waste management and management strategies. These real-time capabilities improve operational accuracy, reduce human errors, and enhance the overall waste handling workflow [21].

A blockchain that ensures the waste management process's traceability and transparency makes this integration possible: Blockchain creates unchangeable records of each stage of the waste disposal lifecycle, from family to final disposal, using a decentralized ledger. These immutable records support accountabilities, improve regulatory compliance, as well as offer stakeholders an auditable trail [21]. Moreover, smart contracts technology in blockchain platforms can help automate essential regulatory inspection and reporting processes, thus drastically reducing administrative burden while remaining in compliance with environmental and legal standards. Artificial intelligence, IoT, and blockchain together make a powerful and secure framework for sustainable waste management in healthcare facilities [22].

4.3. Policy and Regulation Support

However, an enabling policy and regulatory mechanism is crucial in inducing the adoption of AI-based hospital waste management solutions. Broad standards to define waste classification and the corresponding waste management treatment will help to facilitate uniform and responsible adaptation of AI technologies across various healthcare facilities. Such kind of Framework provides precise directives for deploying Artificial Intelligence in existing waste management systems, ensuring adherence to safety & environmental standards.

To promote AI-based solutions in hospitals facilities, governments and regulators can also provide subsidies and grants, and tax benefits for adoption of AI-based solutions. The cost-saving PCI and ROI lead to a lower total cost of ownership, making advanced technology more affordable for resource-limited healthcare organizations. Along with financial measures, policy initiatives should prioritize funding for RESEARCH and development, RESOURCES for healthcare worker skilling, and INVESTMENTS in any basic digital infrastructure needed to make the health system interlinked. These measures make an enabling environment for emerging technologies, increase the deployment of AI technologies, and enable more sustainable and efficient hospital waste management procedures [23].

4.4. Collaborative Research

Collaboration is key to driving the implementation of AI management solutions in hospitals and addressing overarching challenges. Technology developers, advanced healthcare companies, and government agencies can collaborate to establish a robust framework akin to a comprehensive regulatory reform, fostering accountability in technology deployment. This framework could create an ideal environment where interdisciplinary scientists work together to develop transparent, ethical, and responsible solutions. This partnership ensures that AI technologies are not only innovative, but also in step with the fundamental needs and regulatory demands of the advanced healthcare ecosystem.

Other means of technology promotion include stakeholder data set sharing and best practice sharing. Having access to the highest degree of standardized and “clean” data sets opens up the design and development of AI models at an exponential rate, and sharing insights on successful implementations can help departments tackle widespread issues. Public-private partnerships (PPPs) are essential in keeping the chasm between technology advancement and its application in the field, optimizing both the resources and knowledge of both sides to drive progress.

International cooperation can use these efforts by keeping in mind about global knowledge, financial, and latest technological resources. Cross border initiatives can help address data privacy, establish common standards, and promote the adoption of sustainable waste management. Through collaborative research and partnerships, contributor can create a powerful framework to integrate AI technologies into hospital waste management, driving innovation and real impact.

5. Conclusion

Artificial intelligence and machine learning offer transformative potential to improve hospital waste management by increasing efficiency, accuracy and sustainability. Despite challenges such as data limitations, technical complexities, and economic constraints, technological advancements and collaborative efforts can deliver significant benefits. Future research and development should focus on creating scalable integrated solutions to meet the unique needs of medical waste management systems. By leveraging artificial intelligence and machine learning, healthcare organizations can move towards a more sustainable and efficient waste management model.

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Research Article

Selecting Suitable Requirement Elicitation Technique for Development Methodologies

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Abstract: Requirement elicitation is one of the early stages of requirement engineering and is critical in the success of any software development project. There is several elicitation methods presented in the literature: interviews, surveys, brainstorming and others; all of which have their strengths and weaknesses. However, the selection of technique is normally arbitrary as software engineers tend to choose based on their own past experiences. This paper aims at developing a new method for identifying the appropriate requirement elicitation technique based on certain characteristics of the project. The approach is based on regression analysis that captures the most important factors that determine the choice of the elicitation technique depending on the project domain. A classification and regression tree model is implemented to systematically identify the optimal technique, reducing the subjectivity associated with requirement elicitation.

Keywords: Requirement Elicitation; Regression model; Attribute selection; Model;

1. Introduction

Requirement engineering is one of the fundamental phases of software development life cycle and has a direct impact on the quality and outcome of the Software Product. It is very essential in systematic process where the requirements which form the basis of other activities are identified, documented, verified and controlled. As pointed out by [1], quality of requirements represents a major driver of the cost and time needed to complete the project as well as the success of the project; requirement elicitation was cited as one of primary reasons for project failure.ng, validating, and managing the system requirements that serve as the foundation for all subsequent development activities. As noted by [1], the quality of requirements has a profound impact on the project's cost, timeline, and ultimate success, with poor requirement elicitation being one of the leading causes of project failure. As stated by the Standish Group in the CHAOS Report [2], problems with requirements account for many of the failed software projects, meaning that techniques for requirements elicitation are issues important for success. In the requirement elicitation phase, which is the first phase in the requirement engineering, the primary concern is the identification of the users, client's and other domain experts' needs. In this phase, methods such as interviews, questionnaires, surveys, focus groups, and brainstorming sessions are used, and differ by the application in the project [3]. However, no such technique is generic to be applied across the board as every project has different requirements in terms of size, complexity, distribution of stakeholders and domain specific [4].

It is prerequisite to choose the suitable elicitation technique so that all the requirements are fully and precisely gathered. However, this selection process is rather selective and mainly based on engineers' preferences or even their past experience [5]. Moreover, there is a lack of standard guidelines to determine how the technique best suits the project in question and allows for harmonizing the scope and nature of the applied technique in all the projects that were investigated. In order to overcome these challenges, this paper recommends a best-fit approach of selecting requirement elicitation techniques based on key project characteristics such as size, complexity, stakeholders and domain. This approach applied regression analysis to establish the significant predictors of the affectivity of various elicitation techniques. The proposed method helps to avoid bias and be more revolutionary to select the most appropriate technique for each project and to get more accurate and complete the gathered requirements. An extended predictive model for classification and regression is used for testing the approach with tangible success. Based on the attributes of a project, this model can predict the appropriate elicitation technique to be used from the database of previous similar projects from different domains. Through finding ways of applying this model, then software engineers and project managers will be in a position to select the apt elicitation techniques to meet the stakeholders' needs as they work towards developing the right system product. The choice of an appropriate elicitation technique should therefore be made in order to achieve an accurate and thorough capturing of requirements. However, this selection process is not free from bias where engineers tend to make decisions based on personal bar or previous performances [4]. In addition, there is no accepted practice on how one can choose the appropriate technique depending on the characteristics of a given project; this results into inconsistency in methods used for elicitation across different projects. The remainder of this paper is structured as follows: Section 2 presents a critical analysis of conventional requirement elicitation methods and their drawbacks. Section 3 describes the regression analysis process of choosing the elicitation techniques elicitation. Section 4 highlights the predictive model and provides a validation and performance of the model. Lastly, Section 5 summarizes the findings of this paper whereby the significance of the proposed approach and its relevance to software engineering practice is shown.

The core issue lies in the lack of a structured framework to select the most suitable requirement elicitation technique (RET) for different software development methodologies. This challenge becomes more pronounced when considering safety-critical systems, where improper requirement elicitation can lead to serious safety risks. Existing safety evaluation methods often fail to adequately integrate the specific needs of the development methodologies being used. For example, agile development focuses on flexibility and iterative delivery, which requires elicitation techniques that adapt to evolving requirements. Conversely, traditional methods like Waterfall rely heavily on upfront requirement clarity, necessitating techniques that thoroughly analyze initial user needs.

This misalignment creates several challenges:

- Difficulty in mapping elicitation techniques to the context of specific development methodologies.
- Inadequate identification of safety-critical requirements due to the generic application of RETs.
- Lack of criteria to evaluate the effectiveness of RETs in ensuring comprehensive requirement coverage, particularly for safety aspects.

The presented approach introduces a structured evaluation framework for selecting suitable RETs based on the characteristics of development methodologies and safety requirements. This framework addresses the challenges by:

- Providing a systematic mapping between development methodologies and RETs using a set of predefined criteria, such as adaptability, stakeholder engagement, and safety-critical requirement identification.
- Incorporating a scoring mechanism to assess the alignment of RETs with specific methodology goals and safety requirements.
- Focusing on improving the coverage of safety-critical requirements by emphasizing stakeholder collaboration and iterative feedback, especially for Agile and hybrid methodologies.

By bridging the gap between generic RET application and context-specific needs, our approach ensures that the chosen technique effectively identifies, prioritizes, and addresses safety-critical requirements. This not only enhances the overall safety evaluation process but also aligns requirement elicitation practices with the nuances of modern development methodologies.

2. Literature Review

There are several studies in recent years that attempt to identify methodologies and frameworks for choosing the right requirement elicitation techniques for a software project. Saurabh Tiwari et al. [6] introduced a framework based on the electronic search for three key dimensions: refers to the concept of the people, process and project (3PM). Their approach included using electronic databases with keyword search and manually performing a bibliographic search. They also developed a 3PM matrix for each of the three dimensions and used the relationships with the attributes of these dimensions to choose the techniques. This framework formed a clear check list of the various contextual factors to consider when applying given technique, thus brought the technique choice into the right dimension of the particular characteristics of the project and its team and the development process in question. Li Jiang et al. [7] introduced a simple but comprehensive method called MRETS that involves clustering and decision support. Their work discussed the state of the art in requirements engineering and explored some of the most relevant papers in the field as well as giving recommendation on how to choose elicitation techniques based on type of project. The crucial approaches in MRETS are in clustering the similar types of projects and also decision support systems to decide on the suitable technique. Their comparative assessment revealed that clustering when coupled with decision support mechanisms is a more efficient and effective procedure for the selection of elicitation techniques.

Carrizo et al. [8] carried forward the research by proposing a contextual attribute-based framework to select the requirement elicitation technique. They stressed that each technique should be used with the right attribute value improving the choice of techniques for various project environments. Their approach assists in identifying the best technique based on the characteristics that affect the outcomes of the elicitation process. Anwar et al. [9] considered identifying and applying the appropriate elicitation technique. In their approach, aspects such as the stakeholders' needs, prospects of the technique and characteristics of the working environment were taken into consideration. Thus, to evaluate the impact of these factors and determine how they work together, they have created a procedure that can be used to identify the most appropriate method for a given project environment. Muqeem et al. [10] independently described and theorized a detailed framework for the elicitation process, which was also divided into pre-domain development, stakeholder management, technique selection and prioritization. Their approach also guided the selection of the right technique by considering the evaluation of each component and also the overall alignment of the elicitation process with the objectives and scopes of the project. Jiang et al. [11] categorized the requirement elicitation techniques and presented a knowledge based approach for selecting the most appropriate technique. They use knowledge representation schemas and reasoning mechanisms in their methodology to improve on the aspect of decision making. While this line of approach is informative, the process entails a lack of overshadowing commitment to determining and selecting the most salient attributes essential for technique categorization, which remains an issue in the current literature.

Zowghi et al. [12] presented a six step process for identifying the requirement elicitation technique based on multiple factors that affect the process. Their model expresses the necessity of the assessment of these attributes in order to consider whether the certain technique is suitable for the project.

Recent studies have explored a variety of RETs in different development methodologies, with notable improvements in their application for both traditional and agile software development. However, many of these approaches still face challenges related to adapting to dynamic project environments and effectively addressing safety-critical requirements.

2.1. Recent Studies on RETs and Development Methodologies

A study on automated requirement elicitation methods in agile settings with an emphasis on stakeholder participation and quick feedback loops was carried out by Deep et al. [13]. They provide a machine learning-based method for dynamically adjusting RETs over the course of the program lifecycle. However, their research mostly focuses on functional requirements, leaving out important non-functional requirements that are frequently found in safety-critical and construction domains.

Comparable to the methods employed in our work, scenario-based elicitation strategies were investigated in project management by Islam et al. [14]. But its approach doesn't particularly address safety or project-specific hazards; instead, it concentrates more on generic business needs. By integrating temporal dependencies and modifying the RETs for dynamic building projects, our method builds on their work.

Big data analytics for requirement prioritization was introduced by Wang et al. [15]. Although their approach is very successful at increasing productivity in large-scale software projects, it does not provide comprehensive support for integrating real-time modifications to safety procedures or adjusting to project phases, which is crucial in construction settings. In contrast, our approach integrates real-time data and continuous feedback to address these dynamic changes. Palomares et al. [16] looked at the practical difficulties in requirement elicitation and emphasized how improved techniques could be helpful in dynamic environments like construction. Their findings suggest that adopting data-driven approaches can help bridge the gap between theory and practice, particularly in safety management. Ahmad et al. [17] developed a deep learning-based model for choosing appropriate requirement elicitation procedures, demonstrating its effectiveness in minimizing project failure risks. This approach demonstrates how machine learning models can improve decision-making in complex project environments, which is directly applicable to the construction industry, especially for safety-critical requirements. Zhang et al. [18] looked into how sophisticated machine learning algorithms may anticipate and control risks related to building projects. Their method increased operational effectiveness while optimizing safety, making it extremely pertinent for enhancing construction safety management.

Although these studies have brought in a number of insights, most of the approaches are still limited to being very theoretical and there is absence of fully automated approach to assist in the selection of the most suitable elicitation technique. While there is a lot of literature documented on identification and selection of attributes, there is limited research available for the methodological framework for predicting suitable elicitation technique for projects in different domains of application. This demonstrates the importance of an automation process incorporating problem specific aspects and presenting a quantitative model for technique assessment. Some guidelines and frameworks have been suggested for choosing the requirement elicitation techniques; however, most of them are not supported by tool and do not cover all aspect of requirements elicitation in projects that are dynamic in nature. This highlights the need for a further research in order to work on models which use regression analysis and machine learning methods in order to determine which elicitation technique suitable for a particular project in relation to particular attributes. Our solution clearly incorporates tools to adjust RETs dynamically based on project phase, key task changes, and safety feedback. Our framework offers a more adaptable and responsive approach by modeling the changing nature of safety needs throughout time, in contrast to existing methods that take static requirements into account. Our technique guarantees that safety issues are completely addressed by giving priority to stakeholder feedback at every step of the project, lowering the possibility of missing important safety measures.

3. Requirement Elicitation Techniques

Requirement elicitation is one of the most important and basic activities of software engineering that task is to identify detailed and accurate requirement from customers, users or any experts in the field. The process is to identify both the functional and non-functional requirements that will describe the nature and character of the system. Requirement's documentation is critically important in software projects, as vagueness or incompleteness of requirements usually result in failures. Elicitation process is therefore very vital since it provides understanding of the users' needs and the constraints of the project that define the system. Since the context of one project is likely to be different from that of another project, many approaches have been described in the literature to facilitate the identification of requirements. Although the choice of BCTs remains determined by some of these factors, the specific technique to be used is again bounded by the type of project, involvement of stakeholders, and the overall development method being implemented. This is why it is crucial to choose the right elicitation technique properly to make the requirements gathering phase fast and produce a suitable specification for the development.

Table 1 provides details related to different Requirement Elicitation techniques

Table 1: Elicitation Techniques in Literature

Category	Technique	Description	References
Traditional	Interview	A technique of getting the data immediately from the respondents in a more focused or in a slightly formal dialogical form to reveal their needs and perceptions.	[9], [20]
	Questionnaire	A method where a large group is administered structured sets of questions in order to obtain quick quantitative responses on certain topics.	[21], [22]
	Data Gather from Existing System	Looking back and scrutinizing on current systems, documents and reports in order to discover relevant information as well as measures and patterns.	[23], [24]
	Survey	Like a survey, but more general and usually provides the ability for mathematical analysis of the opinions of the audience.	[25]
Collaborative	Focus Group	An approach used in involving stakeholders in a common discussion on the requirements, needs, or opinions of a project or a product.	[26], [27]
	Brainstorming	A creative group technique aimed at coming up with solutions to problems by allowing participants discuss their ideas further without constructive criticism from other participants.	[28]
	JAD	Joint Application Development is a formal meeting where business users and IT solution implementers congregate to engage in requirements analysis and solution creation.	[29], [30]
	Prototyping	Towards the creation of initial samples of a product where it is used to check on concepts, requirements, and incorporating stakeholder responses.	[31], [32]
	Workshop	A highly focused, tightly orchestrated time of planning in which the stakeholders and their teams gather to explore and negotiate what is needed and achieved.	[28]
	Models	Utilizing graphics or geometry, charts and diagrams, and other methodologies with which processes, data flows, or requirements can be illustrated systematically and clearly.	[33]
Cognitive	Document Analysis	A process of analyzing the documents available in the present or any other previous data report or any text medium to harvest	[34], [35]

		valuable information or to analyse historical data	
	Card Sorting	A technique where structured sets of questions are distributed to a large group to gather information quickly and quantitatively on specific topics.	[36]
	Laddering	A group of questions to help a person dive deeper into a problem, pattern, or desire that seems to be motivating the client.	[37]
Observational	Observation	Observing and documenting the live interactions of the users with the systems or processes in their social context with a view of identifying the behavior and issues.	[38], [39]
	Ethnography/Social Analysis	Culturally, socially and contextually validated users' research in real life settings in order to know how user needs and tasks characteristics are influenced.	[40], [41]

4. Regression Analysis

Regression analysis is a method identified with outlining the most likely condition between independent and dependent variables. In the process of requirement elicitation, regression analysis can by used as a method to determine which attribute or factors (independent variables) contribute most to the selection of elicitation technique (dependent variable). In regression modeling, the models available are the linear models, multiple linear models, and nonlinear models. In assessing data that can be represented through linear dependent variables, linear as well as multiple linear regressions are usually applied. Nonlinear regression on the other hand is used in complicated datasets where equation plotted is not linear.

Linear, as well as multiple linear regression models are used in our study to evaluate the impact of multiple attributes on the choice of the most suitable elicitation technique.

5. Proposed Methodology

This paper aims to present a new approach that is based on both qualitative and quantitative research that can help to determine suitable elicitation techniques for different software development projects. The proposed Research methodology presents a systematic approach adopted in selecting techniques because of specific critical attributes for varying domains for instance web-based, mobile, and desktop applications. The process begins with gathering requirements of a project from various domains and secondly, to assess these requirements in order to determine the needs of a system. The selection of critical attributes that influence the development process is done afterwards. Depending on the elicitation attributes, various techniques are considered appropriate, and if not, the selection process is fine-tuned by use of regression analysis. The preferences derived from the regression analysis are then incorporated in a model, which gives indications on the right approach to use for different kinds of projects and methods.

5.1. Framework Design

A framework is proposed for selecting suitable technique for different methodologies. Fig. 1 provides the phases for the proposed framework design:

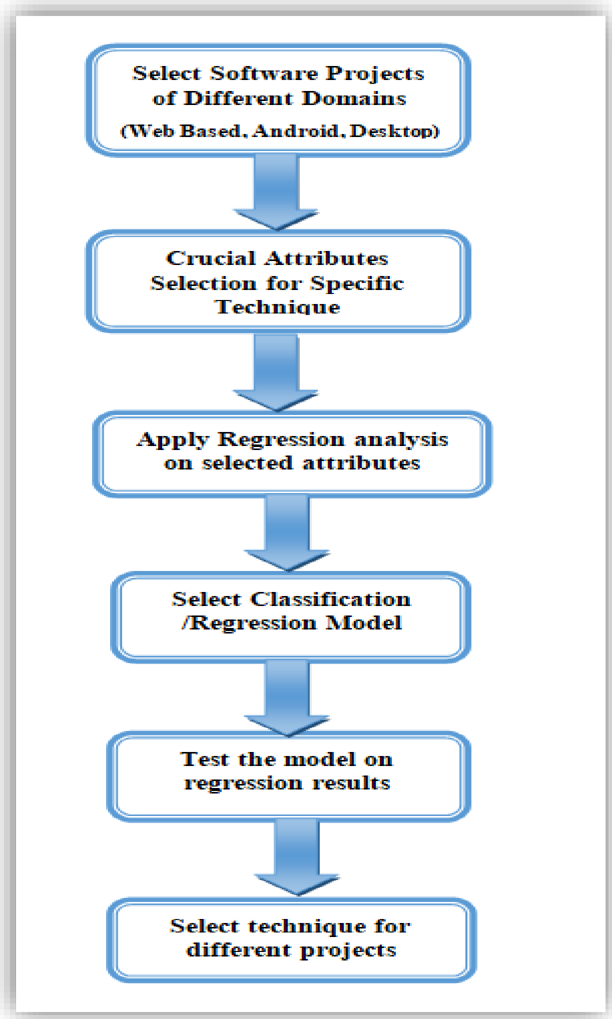

Figure 1: Proposed Framework Design

The framework for selecting the most suitable requirement elicitation technique is designed in three key dimensions: 1. Requirement Selection: Depending on the type of a certain project, the needs are collected and divided into categories necessary for the project's accomplishment. 2. Attribute Selection: All attributes depend on the nature of the project and some of these are stakeholder participation, type of project, and development process. These attributes are central to defining the extent of applicability of a given technique among other elicitation methods. 3. Regression Analysis: Linear regression models are used in making decision in order to determine which of the selected pool of attributes are of the most importance when relating to the technique selection. Classification and regression models are used to predict the suitability of the elicitation technique so that the technique selected for the project would be appropriate.

The ability of the RETs to identify temporal and dynamic patterns in safety-critical situations led to their careful selection. Important methods consist of:

- **Focus groups and interviews:** These methods allow for the gathering of in-the-moment information from stakeholders, capturing temporal dependencies such shifts in safety risks during project phases.
- **Scenario-Based Elicitation:** This method ensures a thorough assessment of how hazards change over the course of a project by using simulated safety situations to comprehend possible risks

throughout time.

- **Ethnography and observation:** Direct observation of building processes yields important time-series data, including task sequences and the safety concerns associated with them. This allows for the identification of temporal patterns that static elicitation techniques could miss.

The chosen RETs provide a number of benefits for assessing construction safety, especially when it comes to handling the dynamic character of building sites:

- **Temporal Insight:** Methods like scenario-based elicitation and observation successfully record how safety risks vary over time, guaranteeing that the assessment takes changing hazards into consideration.
- **Sequential Data Handling:** The framework can detect crucial event sequences that result in safety accidents by integrating methods that emphasize real-time data collection, supporting proactive risk management.
- **Stakeholder Engagement:** By encouraging ongoing feedback through iterative techniques like focus groups and interviews, stakeholders can update and improve safety criteria in response to changes in project dynamics over time.
- **Situation-Aware Risk Analysis:** The capacity to gather and examine data in real-time guarantees that the safety assessment stays in line with the particular situation and timeline of the construction project.

5.2. Requirement Gathering Phase

During this phase, software projects from different domains (Web-based projects, mobile applications, and Desktop systems) are chosen for the experimentation process. These projects are selected because they implement various development models inclusive of the Waterfall, Incremental, and Prototype models. Collection and analysis of the requirements for each project is made in order to understand how they sit with the corresponding methodologies. For all the projects elicitation techniques are selected depending on their correspondence to the project’s characteristics and the chosen development model.

5.3. Subset of techniques

Following techniques are selected for our proposed approach:

- Brainstorming
- Interview
- Focused groups
- Workshops
- Observations
- Prototyping
- Questionnaire
- JAD
- Survey
- Task Analysis

5.4. Attributes Selection

The choice of the significant characteristics is made according to the gathered demands on projects in various fields. The following are some of these attributes which are critical in identifying which elicitation techniques are most relevant to a specific project type.

1. Project-related characteristics encompass the type of project, its category, as well as specifics of a particular project.
2. People-related attributes center more on people who are directly or indirectly implicated in the project and issues, relating to them.
3. Product-related attributes refer to the characteristics of the ultimate software product, process that

was used while developing the system, the development methodology being Waterfall, Incremental, or Prototype.

Table 2: Attribute Selection

Type of project	Real time/distributed/interactive/information system
Size of project	Big/Medium/Small
Project status	New/Existing
Stake holders	Single/multiple
Stake holders' involvement	Maximum/average/minimum
Team size	numbers
Resource constraints	Critical/high/medium/low
Time constraint	Critical/high/medium/low
Cost constraint	Critical/high/medium/low

Table 2 provides a list of selected attributes for elicitation technique selection process.

6. Multiple Linear Regression Model

In this section the choice of elicitation techniques is analyzed with the help of multiple linear regressions to determine the significant factors. Multiple linear regressions enables the analysis of more than one independent variable (features of the project, characteristics of the stakeholders, development procedures) with reference to one dependent variable (elicitation technique). To compare these variables, ANOVA (Analysis of Variance) is used to determine the existence of significant predictors.

The simple Linear equation is as following:

$$Y = a + b X + \mathcal{E} \tag{1}$$

Where Y is dependent variable, X is independent variable, a is intercept, b is slope and Ɛ is residual.

Requirements were collected from different projects related to different domains. Waterfall, incremental development and prototype were used in majority of these projects. After analyzing projects requirements, following is the detailed relationship of the attributes according to the techniques:

Table 3: Project Attributes

Elicitation Technique & Attributes	Type of project (Real time, distributed, Interactive, IS)	Size of project (Large/ Medium/ Small)	Project status (New, Existing)	Stakeholders (Single, Multiple)	Stakeholders involvement (Max., Avg, Min)	Resource constraints (Critical, High, Medium, Low)	Time constraint (Critical, High, Medium, Low)	Cost constraint (Critical, High, Medium, Low)
Brainstorming	R/I	M/L	New	M	Max.	L	L	L
Interview	R/D/I	S/M/L	New/Ex	M	Avg./Max.	L	L	L
Focused groups	R/I	S/M/L	New/Ex	M	Max.	L	L	L
Workshops	D/I	M/L	New	M	Min.	H/L	H/L	H/L

Observations	I/D	S/M/L	Ex	S/M	Min./Avg.	L	L	L
Prototyping	R/I	S	New	M	Avg./Max.	L/H	L/H	L/H
Questionnaire	R/D	M	New/Ex	M	Min./Avg.	H/C	H/C	H/C
JAD	I/R/D	M/L	New	M	Avg./ Max.	M	M	M
Surveys	D	L	New	M	Min.	L	L	L
Task Analysis	R	S/M	New	S/M	Avg.	M	M	M

Where the explanations of the abbreviations used in the table are as following:

- R/I: Real-time/Interactive
- R/D/I: Real-time/Distributed/Interactive
- D/I: Distributed/Interactive
- S/M/L: Small/Medium/Large
- New/Ex: New/Existing
- M: Multiple
- S/M: Single/Multiple
- Avg./Max./Min.: Average/Maximum/Minimum
- L/H: Low/High
- H/C: High/Critical

7. Results

The regression analysis was performed on the selected project, people and process attributes to determine the choice elicitation technique for various software development projects. The statistical models were tested to check the fitness of the models the significance of individual attributes and testing of the technique selection with high accuracy. Table 4 and Table 5 below shows the analysis results from the regression model which clearly pointed out a high significance between the chosen independent variable and the chosen technique. The Adjusted Multiple R of 0.9871 shows a very high correlation level between the independent variables (elicitation technique) and the dependent variable. The R Square of 0.9835, indicate that the model is able to account for 98.35% of the variance in the technique selection and thus accounts for the most sources of technique selection. The Adjusted R squared gives the level of determining of the model at 0.8023, meaning that even after the numbers of the variables in the model are considered, the value is still high, and this point to the reliability of the model. These high values suggest that the selected project, people, and process attributes contribute the most to the selection of the elicitation technique. Thus, the estimated coefficient which is about 1.5234 from Standard Error indicates that there is still some variability that has not been explained by the model and it perhaps owes to other project characteristics or some other variable which has not been captured in the model.

Table 4: Regression Analysis Results

Regression Statistics	
Multiple R	0.9871
R Square	0.9835
Adjusted R	0.8023
Standard E	1.5234

Table 5: ANOVA Statistics

ANOVA			
	df	**SS**	**MS**
Regression	20	12.455	1.245
Residual	8	0.245	0.0023

The regression model is also given an analysis of variance in the ANOVA table as shown in Table 5. The obtained bigger F-statistic level and smaller p-value indicate that the overall regression model is statistically significant and aids in the end-to-end technique selection. It shows that the regression model is quite successful in explaining a considerable amount of the data variance in general terms. In table 6, the results of the regression coefficients of each attribute estimates offer an additional understanding to the amount each of the variables influence to predict the elicitation technique. This means that the p-values produced represent a sign of the statistical importance of an attribute. Variables with p-v >= 0.05 are less relevant in the prediction model while the variables with p-v < 0.05 are significant in the prediction model.

- **Project-related Attributes (e.g., project type, complexity, scale):** These variables had high p-values thus signifying that their influence was not as huge as those of the other attributes. Nevertheless, they also help to provide important contextual information to the technique selection process.
- **People-related Attributes (e.g., stakeholder involvement, experience):** This group had significant low p-values and therefore the hypothesis test results demonstrated a strong significance especially on Stakeholder Involvement hence the engagement level of stakeholders has a significant influence to the selection of elicitation techniques.
- **Process-related Attributes (e.g., development model, process maturity):** Regardless of their statistical significance, the modeling results conveyed the importance of aligning process characteristics with the development process when selecting an appropriate technique for requirement elicitation.

Table 6: Coefficient Analysis

	Coefficients	**Standard Error**	**t Stat**	**P-value**
CT1	1.045721	1.392872	0.750142	0.034564
CT2	2.148391	2.634821	0.816957	0.000298
CT3	1.432198	3.276935	0.692506	0.009121
CT4	0.572430	1.211346	0.472063	0.848721
CT5	1.389456	1.539384	0.188695	0.008451
CT6	1.506721	3.034258	0.742172	0.007851
CT7	0.684299	0.594032	1.150126	0.122073
CT8	0.976491	1.312678	0.743231	0.005689

Significant Variables: Analyzing the p-values it is clear that the variables CT2, CT3, CT5, CT6, and CT8 are significant, which the p-values are less than 0.5.

Insignificant Variables: CT1, CT4 and CT7 take relatively higher p-values in the structure and they are less significant. The regression outcome brings out that method selection depends on key attributes like the participation of the stakeholders (CT2, CT3), the process model adopted (CT5, CT6) and the type of project

(CT8). The R-square statistic which is relatively high points to the fact that the model can predict with precision the most suited elicitation technique given the recognized attributes.

8. Model Design

This section presents a model for identifying the critical attributes that influence the process of elicitation techniques selection by a multiple regression analysis. Following is the proposed model to select the elicitation technique on the basis of critical attributes.

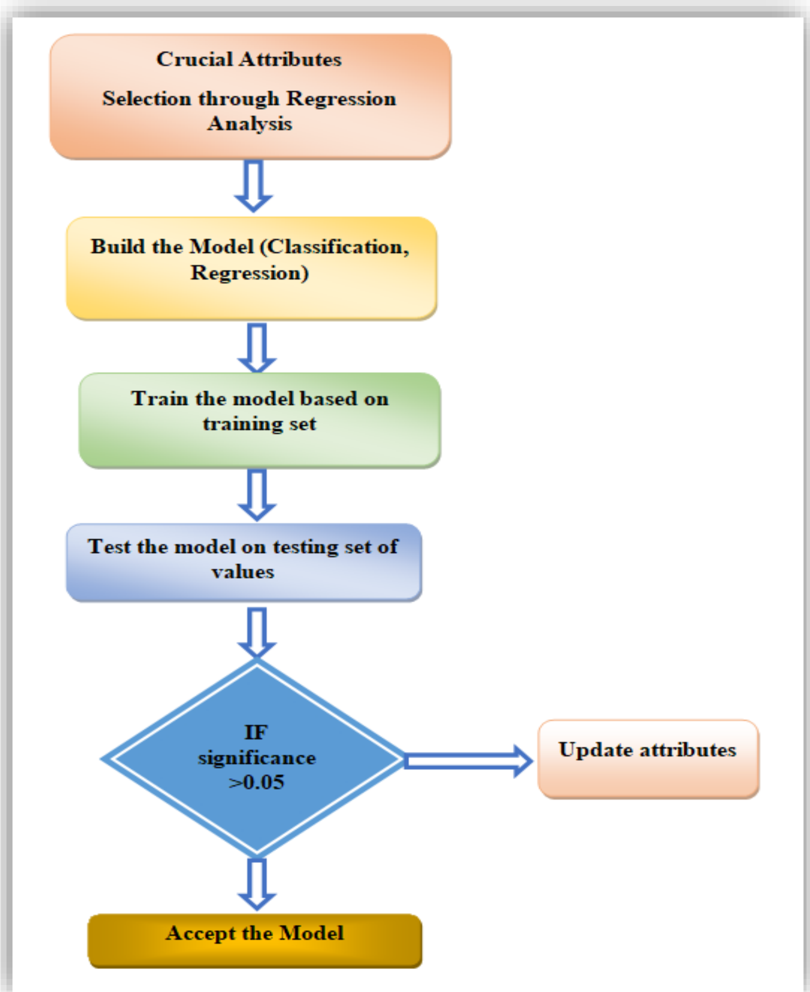

Figure 2: Proposed Model for Technique Selection

This section outlines a model that hopes to facilitate the determination of the decision factors that define the elicitation techniques in software development. In the research proposed here, multiple regression analysis will be used to investigate the extent of association between project characteristics and the suitability of particular elicitation techniques for a project. The developed model has the intended capability to estimate the technique that offers the best fit in a given project context with regard to project, stakeholder, and process characteristics and is generically applicable to various software development paradigms. Methodology The model comprises of a regression analysis of the selected attributes that form the basis of the system. The outcome of this analysis using classification or regression is the result form part of the inputs to the model. The p-values of each attribute with set at 0.05 are used to identify its relevance in the model. When the p-value of an attribute is equal obtain a value greater than 0.05, then that attribute is discarded from the analysis due to insignificance. On the other hand, attributes with a p-value of <= 0.05 thereby considered relevant in the elicitation technique choice. The dataset is split into two subsets: Squares of the data are split into 70/30 ratio in order to both train the model and check its reliability for prediction. If the testing results indicate that the significance the selected attributes is higher than the predefined level ($p<0.05$), then this attribute is excluded. If the model gives the correct predictions of the technique selection based on the remaining important attributes, then the model is said to be valid.

9. Discussion

Based on the regression analysis and the criteria described, the following elicitation techniques are recommended for different types of software development projects: The most appropriate methods of requirement elicitation are interviews, focus groups, workshops, observation, and prototyping. These techniques are suggested because they reflect the web-centred and multi-stage character of web-based systems where the prominence of user feedback and subsequent fine-tuning is warranted. For Android development projects the best practices are interview, focus groups, ethnography (watching & listening), idea generation and brainstorming sessions, workshops. Meanwhile, these techniques are especially useful when studying such aspects of user behavior as the need for the specific portfolio-oriented requirements for the mobile systems. Strategies that are considered appropriate for elicitation in the development of the desktop applications include: interviews, focus group discussions, workshops, observation techniques which involves ethnography, modeling, questionnaires and surveys. These are the best methods when it comes to capturing all the needs of the user and making sure that all the needs of the system are captured systematically.

10. Conclusion

The approach presented in this paper is a method for predicting the most appropriate elicitation techniques for a given software development project. To that end, the method starts with the review of literature in order to compile the different requirements from various projects to establish essential attributes. These attributes are chosen depending on the relation to elicitation process and a significance of its affecting technique choice. Classifying these attributes as significant to the selection of the elicitation technique and as insignificant, multiple linear regression analysis was employed. Based on the critical attributes, the proposed model uses them to determine the most appropriate technique for effective project classifications. As a result, it seems that more accurate and complex techniques may be worth trying in the future, which would involve applying machine learning or artificial intelligence approach to enhance the accuracies of the proposed method. Furthermore, expanding the validation of the model on various elicitation methods across more extensive projects will offer additional confirmation and fine-tuning of the suggested approach in the area of requirements engineering. For future work, it should be possible to add other relevant project related features in order to build an enhanced model as well as test the model on more project types and domains.

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Research Article

Fake News Detection using NLP and ML Techniques

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Abstract: Effortless access to the bulk of information and its spread is becoming a major issue these days. Many people rely on social networking sites and electronic media to get information. These sites might be used to spread information more quickly, especially fake information. This widespread has catastrophic results on individual and society. Identifying the fake news over numerous mass media platforms have rendered traditional machine learning algorithms less effective. Since fake news detection is vital, this study aims at analysing common machine learning algorithms- linear regressor, decision trees, random forest and Naïve Bayes, MLPC and LSTM and the ensemble methods- XGBoost and CatBoost, particularly to validate the efficiency of Kaggle dataset on fake news (fake-and-real-news-dataset). The results reveal a surprising lead of ensemble methods and LSTM over other algorithms in this dataset, particularly the XG Boost Classifier achieved the highest accuracy of 92% in validation and 100% in training. Similarly, Recall score of CatBoost is higher than others.

Keywords: Fake News; Text Processing; Machine Learning;

1. Introduction

Exponential growth and informal access to the information available has made it complicated to differentiate between incorrect and correct news. The prevalent diffusion of data has ironically promoted an exponential increase in its deformation. [1]. Endorsing data validity in modern times is becoming an issue of raising concern. The propagation of any false information in society has determinantal effects on a community. Nowadays, search engines and social media have become the primary sources of news for many people, surpassing print media. It can be said undoubtedly that publishers have no control on information flow due to bulk of information and news accesses through electronic media. Social media possesses unmatched reach and influence, enabling it to impact billions of people worldwide. Fake data entail verifiable, misleading, and purposefully false information. There is a severe need of a system to ensure that the information exchanged is genuine or spreader is honest. With no active monitoring the news spread can be molded by the people or community for their own needs and can cause detrimental effects on a community [2]. Misinformation often spreads more rapidly than factual news, as it is often tailored to be more engaging and attractive to audiences. Different types of fake news include fabricated political stories, misleading ads, sensationalized rumors, and mock or satirical articles. Google publicized an innovative facility named "Google News Initiative" intended to track and eliminate misinformation. During the 2016 US presidential election, numerous articles circulating online contained false information and misleading data, which spread rapidly and gained widespread attention. As a result, distrust took hold, increasing partial reviews and backing up biased public perception. Such misleading information poses biased opinion that creates hoax among people mind therefore controlling the decision e.g., the political election [3]. As a result of such serious concern about social and national damage, considerable research attention is already being devoted to this field. Advances in natural language processing and machine learning have empowered the creation of complicated models capable of classifying between true and false news stories [4].

Developing a fake news detection model is challenging. The goal of these models is to classify news articles as fake or real by outlining insights gained from a comprehensive review of previously verified fake and real news stories. The readiness of large news datasets is decisive, and news articles can be sourced from various online platforms, including search engines and social media sites. Still, defining the news authenticity can be stimulating and time-consuming task if done by hand. On the other hand, fake news detection can be viewed as a binary classification problem or a fine-grained classification task. Following 2017, researchers have made rigorous efforts to improve model performance using assorted widely available datasets. Although no single benchmark dataset has been widely adopted, several prominent datasets are commonly used are CREDBANK, BuzzFeedNews, LIAR, PHEME, ISOT, PolitiFact, BS Detector and Kaggle.[5].

The substantial amount of heterogeneous content is available and advancement of natural language processing and machine learning techniques we can improve, pace up, and standardise the methodical process of such problems. Unstructured text data holds valuable insights, which can be uncovered through the synergistic application of NLP and ML. This paper demonstrates the efficiency of the combined approach in classifying fake news, using a labeled dataset from Kaggle. Through a comprehensive evaluation of existing techniques, we developed a better model to improve classification performance. Our methodology necessitated calculating TF-IDF features prior to model training, which was ensured using a variety of machine learning techniques. The model achieved the highest accuracy score achieved is 92% when keras vectorizer is used on data set. All the model results were above 95% with simple TF-IDF vectorization.

Section II explains the background knowledge and survey of the relevant content. Proposed model is given in Section III which discourses the approach to detect the fake news from the real ones using basic NLP processing on dataset and applying LSTM to tarin and test the model. Section IV concludes the discussion, and references are provided in Section V.

2. Literature Review

Reference [2] provides an exhaustive examination of the key characteristics involved in detecting fake news, along with a complete analysis of various machine learning techniques and their applications among different news categories. Comparative studies on fake news detection approaches and datasets showed that content type, whether textual or image-based, impacts the choice of method, eventually leading to better problem-solving and improved classification performance. The work on the image type news is still an open challenge as the reliability and impact of the spread depends a lot on the content type i.e., text or image. News articles frequently feature multimedia components, such as images and videos, that are not inevitably connected to the content, but are designed to tempt readers with clickbait tactics.

The paper [5] presents analysis of four machine learning techniques based on accuracy score and convergence time. The Naïve Bayes, the neural network, the random forest, and the decision trees algorithms are used for fake news detection. The dataset was trained and analyzed to determine which algorithm executes well. Naïve Bayes algorithm performed good on textual data. The algorithm utilizes Bayes' theorem to calculate conditional probabilities, enabling it to classify between events or classes based on individual text occurrences. Notably, this approach yields better results compared to other algorithms when used on this dataset. The accuracy is decent, and the convergence/training time of the Naïve Bayes is 1.3s which is best as compared to the other algorithms: Random Forest 54.3, neural network 420.2 and Decision tree 520s.

The study [6] developed and evaluated various fake news classification models using machine learning, deep learning, and natural language processing techniques. The scholars compared the performance of four traditional algorithms (binomial logistic regression, naive Bayes classifier, support vector machines, and random forest) and three neural network models (CNN with GlobalMaxpool, CNN with DepNetwork, and LSTM). They also examined the impact of NLP methods such as TFIDF, Word2Vec, and Tokenization on model performance. The results steered that random forest achieved the highest accuracy among traditional methods, while CNN with GlobalMaxpool went best among neural network models. The use of NLP methods significantly improved model accuracy, with traditional methods achieving over 85% accuracy and neural network models achieving over 90% accuracy.

In [7], authors concluded that bots' usage can be perceived as facilitators of information broadcast, either with bad intention or the good ones. They don't benefit from any type of entry; however computational capabilities of the bots are better at disseminating data at faster rate as compared to human beings. In context of its popularity, easy manufacturing, and due to simple usage, they are adopted by many users. There are many ways to improve information authentication but, it requires a great deal of preprocessing of related elements and topologic assessment of items. The reviewed state-of-the-art automatic detection models are composites of natural language approaches and machine learning techniques. According to the authors, natural language processing methods employed in literature serve as a foundational step rather than a complete solution but are commonly incorporated into broader machine learning solutions. This systematic literature review recommends that a hybrid approach combining traditional techniques, orchestrated by a neural network, is the most operative method. They also insisted on unification of different terminologies and definition of fake news domain in lieu of uniform domain ontology. The dearth of consensual information could mislead suppositions and judgments.

The study in [8] explores fake news detection through a two-step approach: classification and discovery. The classification step outlines the fundamental concepts and principles of fake news, while the discovery step reviews existing methods for detecting fake news using supervised learning algorithms. The results show that Naïve Bayes achieves accuracy rates ranging from 74% to 96.8%, while SVM and neural networks reach accuracy scores of up to 99% on Kaggle and various datasets. A study on 2012 Dutch elections fake news on Twitter employed 8 supervised machine learning classifiers. The decision tree algorithm yielded the best results, achieving an impressive F score of 88%. Additionally, some detection models utilizing N-gram analysis attained the highest accuracy score of 92%. Most research papers have utilized the Naïve Bayes algorithm, achieving prediction precision between 70-76%. While these studies primarily employed qualitative analysis, focusing on sentiment analysis, titles, and word frequency repetition, the authors suggest that incorporating quantitative approaches, such as POS textual analysis, could enhance feature extraction and improve precision results using random forest algorithms. The proposed feature set includes a range of linguistic and stylistic metrics, including Lexical features: total words, total unique words, and Type/Token Ratio, Syntactic features: number of sentences and average sentence length, Character-based features: number of characters and average word length, Semantic features: part of-speech tags (nouns, prepositions, adjectives, etc.)

Fake news term is used of any fabricated, doctored, or fake content shared via any medium. Authors of [9] state that unverified news has been escalating at a rapid rate which is alarming for society. It is becoming very difficult to filter the real news from the fake ones. They proposed a solution to detect the fake news automatically through linguistic analysis and machine learning approaches.

Jain et. al., mentioned in [10] that there must be a sophisticated system for detecting fake news as most of the persons use their mobiles to read the news on social media platforms and same medium is playing an important role in spread of wrong information within no time. This paper focuses on detection models that make use of natural language processing and machine learning techniques. like Naïve Bayes Classifier, SVM etc. and achieved state-of-the-art results.

In [11] the discussion is focused on fake profiles on the social media platforms which are spreading wrong information on the internet, and most of the people believe that information blindly. Bots are employed which are generated via Machine Learning techniques and behave like real users. There must be a model that can differentiate fake accounts and real accounts. A very little research exists on detecting the fake profiles created by the human being, especially on SMP's. The previously formed methods though feature engineering is not very useful to detect fake accounts. Every human being has unique thinking and different style to use the social media account. So, bots are always not successful, as they use specific patterns all the time.

The analysis in [12] enforces the development of intelligent systems that can be used to solve complex problems based on implicit knowledge. This survey emphasizes the use of knowledge engineering in development of fake news detection model. According to the authors existing solutions are helpful in overcoming the stated issue but data driven approaches and knowledge engineering can improve the efficiency of existing solutions.

This paper [13] conducts a thorough evaluation and comparison of various fake news detection methods, spanning traditional machine learning approaches, such as Naive Bayes, and popular deep learning approaches, including CNN and RNN. The study reviews a diverse range of data items, including visual, user, network, post, knowledge, style, and stance-based features. The evaluation is performed on three feature sets, and the results underscore the importance of feature selection in achieving optimal accuracy and performance.

While simple approaches yield promising results, the study highlights the potential for complex models to significantly improve accuracy. Reference [14] used probabilistic latent semantic analysis to detect fake news. The study also exhibited a comprehensive comparative analysis of existing literature and estimated various machine learning and deep learning approaches on three datasets. The comparison revealed that deep learning techniques go beyond traditional machine learning techniques in performance, with Bi-LSTM achieving an accuracy score of 95%. The analysis primarily focused on textual data but can be extended to image data and heterogeneous datasets.

The primary objective of the research presented in [15] is to develop a deep learning-based style for detecting fake news. Given the disturbing prophecy by Gartner that most people in mature economies will consume more false information than true information by 2022, automated fake news detection has become a pressing task. The proposed approach addresses the boundaries of existing binary classification models by introducing a neural network architecture, TF-IDF-DNN and BoW-DNN, which accurately predicts the stance between a given pair of headlines and article body, accomplishing an accuracy score of 94.21% on test data.

Reference [16] presents a comprehensive comparison of recent benchmark datasets and experimental results obtained using various methods. It presented fake news detection problem as challenging practical problem of NLP and discussed the existing NLP solutions and their weaknesses. They recommended the appropriate handling of non-textual data and demanded to check whether the handcrafted features can be employed with neural networks. Comparing multiple techniques on different data sets, LSTM based models achieved higher accuracy on LIAR data set as compared to CNN.

On FEVER dataset attention-LSTM has the best score. The experimentation centered on semantic matching of each sentence from reclaimed pages and the entitlement. Another dataset analyzed is Fakenewsnet. This dataset is collected from two different sources: Buzzfeed and Politifact. It mostly comprises of social engagements data from the articles of Twitter. Castillo. The maximum achieved accuracy score was given by GCN. This method takes advantage of graph-based data that encodes associations between news stories and their publishers, using this information as input for a CNN to evaluate the integrity of news articles.

Authors encourage extending this problem of binary classification to multiclass classification problem, where news must not be only categorized as strictly true or false, but the labels must include half true, mostly false etc. Concluding, the accuracy scores can be improved if meta-data including speaker credibility and social engagements' information is also considered.

3. Proposed Methodology

This section presents the experimental methodology, which includes dataset preparation, workflow design, and model training. Figure 2 provides a visual representation of the experimental process. The procedure includes three main stages: data preprocessing, preparation of machine learning and neural network models using traditional and neural network approaches, and a evaluation of the used techniques.

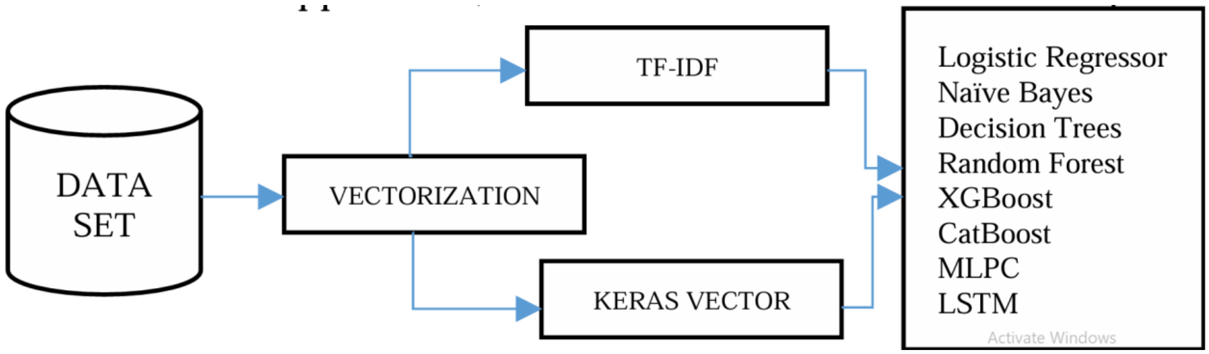

Figure 1: Workflow of Fake News Classification Using Feature Extraction Methods and Machine Learning Models

3.1. Data Set

The Kaggle dataset is used for model training. The dataset comprises 40,000 articles, evenly divided between fake and real news, with each category consisting of approximately 20,000 articles. This dataset consisted of two csv files: fake with 21417 samples and true news with 23481 news samples. Both records consisted of four features. The class label assigned to fake and real news as 0 and 1 respectively, and files are merged for preprocessing of data as a single unit.

3.2. Data Pre-Processing

We investigated to check the missing values in dataset as it affects the overall performance algorithms; no missing values were found. Then data is visualized on subject type for getting the insight. It is clear from the Figure 1 that the data set contains fake news of some categories and real news for other type of categories. The fake and real news are not categorized within the same subject.

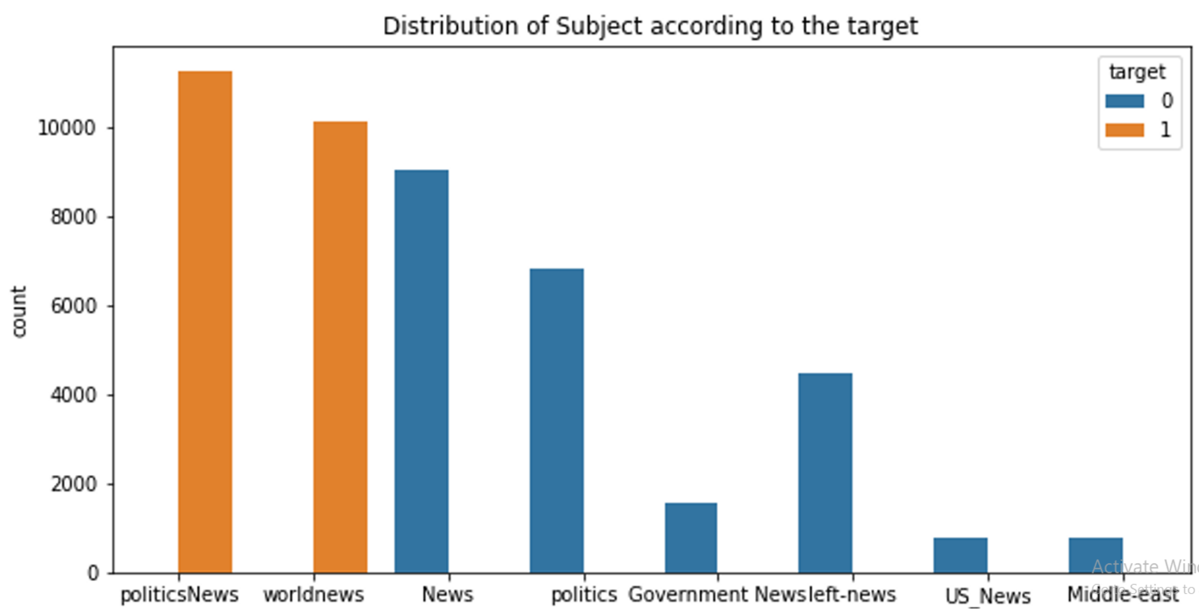

Figure 2: Distribution of True vs Fake News in the Different Subjects

In the next steps all the attributes are concatenated in one content text (news subject + news title + news text) and html content is removed. Next all the punctuation and special characters are removed. Non alphabetic characters are replaced with spaces and all the text is converted into lower case letters. After tokenizing the text into individual words, stop words are removed from the dataset. This is because stop words, such as common function words, are equally likely to appear in both true and fake news articles, representing them useless in distinguishing between the two. Following, we applied lemmatization is applied to bring back multiple form of words/tokens to their common root.

3.3. Text Analysis

After the data is ready, frequent words are looked at using the word cloud. For that all the tokenized text is converted into strings in separate columns because it is to be used later for model training and text analysis. From the word cloud it's clear that there is a detach in progressively diminishing rate of recurrence. The frequency is either elevated or muted in fake news as compared to real ones. iv. Vectorization of Processed data After the examination, the term frequency-inverse document frequency is computed using TFIDF-vectorizer and data is spitted into training and testing samples as 80-20. Another approach of vectorization is deployed in which keras tokenizer is used. This vectorizer enables the conversion of text into a numerical format, creating either a sequence of integers or a vector comprising binary coefficients that correspond to each token. After updating the internal vocabulary for manuscript, text corpus is converted into a sequence of integers and padded to ensure that all sequences in a list have the same length.

3.4. Model Training

The classification models used in this research were Logistic Regression, Random Forest, Naïve Bayes, Decision Trees, CatBoost, XGBClassifier, MLPC, and LSTM. Training these models involved tuning their parameters, resulting in varied outcomes. Subsequently, the trained models were tested on a separate dataset, with a train-test split ratio of 80:20.

4. Results

The scope of this study is to analyze and classify the Kaggle dataset, which confines labeled fake and real news articles. The data is first pre-processed using natural language techniques, and then various evaluation techniques are applied. The results of these evaluations, which involve six different algorithms, are presented in a confusion matrix. The development and testing of the model involved the use of eight machine learning algorithms: Logistic Regression, Naïve Bayes, Decision Trees, Random Forest, XGBoost, CatBoost, MLP, and LSTM. The data set is given in two different forms of vectors and simple TF_IDF vectorization shows better results as compared to Keras tokenizer. Only LSTM performed better in the case of keras tokenizer, where MLPC has shown the lowest accuracy score. The results are summarized in the table below.

Table 1: Results

Model	Accuracy		Precision		Recall	
Logistic Regression	60	99	59	98	51	99
Naives Bayes	58	94	56	94	59	93
Decision Tree	75	99	67	99	95	99
Random Forest	85	99	86	99	82	99
XG Boost Classifier	92	99	88	99	94	99
Cat Boost Classifier	90	100	85	100	97	100
MLPC	54	99	83	99	7	99
LSTM	80		76		8	

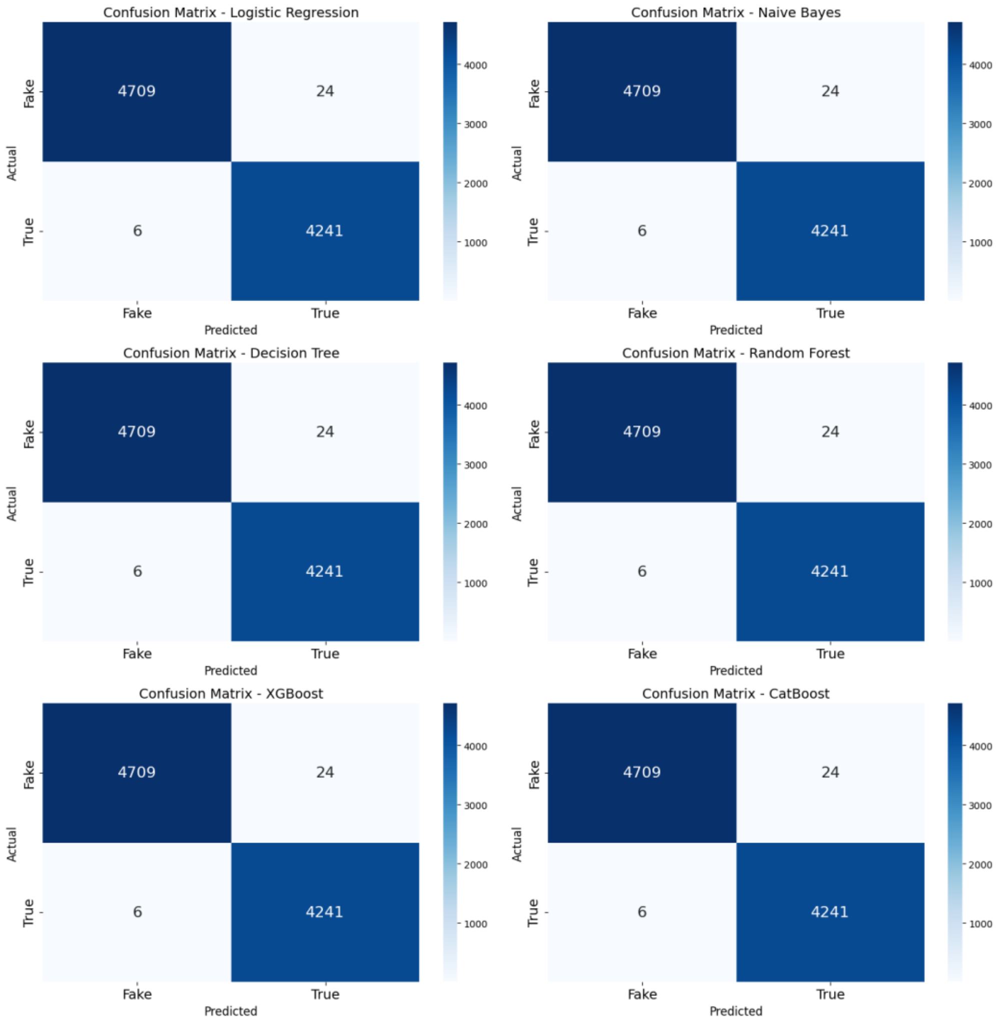

Figure 3: Confusion Matrices of Different Machine Learning Models for Fake News Classification

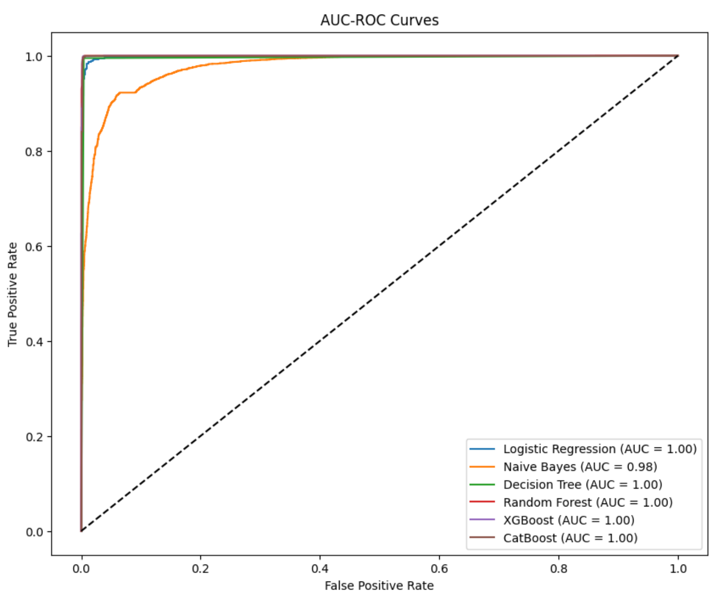

Figure 4: AUC-ROC Curves of Selected Machine Learning Models for Fake News Classification

The confusion matrices for selected classification models are presented in figure 3. Each confusion matrix evaluates the corresponding model's performance in distinguishing fake news (0) from true news (1). The figure shows that all models perform exceptionally well on the selected dataset, showing high accuracy. We also generate ROC for the selected models as shown in figure 4. Although the Naïve Bayes model performs slightly worse (AUC = 0.98) but most of the models show perfect discrimination (AUC = 1.00) True Positive Rate (TPR) and False Positive Rate (FPR). It is likely due to strong learning from the dataset. AUC values close to 1.00 indicate high accuracy, but models should be tested on new data to ensure generalization and avoid overfitting concerns.

5. Conclusion

This study points to develop an effective approach for detecting fake news, employing the combined strengths of NLP and ML techniques. In the first step the data textual data is preprocessed using NLP techniques. After cleaning the data, it is vectorized using keras vectorization technique and simple TFIDF computation. Results were better in the case of TF-IDF vectorization. The maximum accuracy score achieved is 92% using XGBoost Classifier while MLPC has the lowest accuracy score when applied to keras vectorized data set. On the TF-IDF feature vectorst, the maximum accuracy score is given by CatBoost classifier and all the classifiers have values above 95%. For future different feature vectors analysis and K-cross validation can be applied to achieve better results in case of the models that failed to achieve better accuracy.

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