An Ensembled hybrid learning approach for Female Depression Detection

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***Abstract*— Over the past century, significant changes in lifestyle have occurred, contributing to an increased prevalence of depression. Factors such as urbanization, technological advancements, changes in work patterns, and social dynamics have all played a role in this trend. Despite advancements in the detection and treatment of depression, a considerable number of cases still go undetected, leading to untreated suffering and potential long-term consequences.**

To address this challenge, automated systems have emerged as promising tools in aiding the detection and management of depression. Among these systems, language analysis stands out as a crucial component. By analyzing written or spoken language, these systems can detect patterns indicative of depressive symptoms, offering a non-invasive and accessible means of screening individuals for further evaluation.

Text classifiers, a type of automated system, are specifically trained to identify linguistic markers associated with depression. These classifiers use machine learning algorithms to analyze linguistic features and predict the likelihood of depression based on textual input.

This article delves into the comparison between two approaches in text classification: hybrid and ensemble methods. Hybrid models combine different types of features, such as linguistic, semantic, and syntactic, to enhance the accuracy of depression detection. By leveraging a diverse set of features, hybrid models aim to capture a broader range of indicators associated with depression.

On the other hand, ensemble models take a different approach by combining multiple individual classifiers to make predictions. Each classifier may use different algorithms or feature representations, and the ensemble aggregates their outputs to arrive at a final prediction. This technique often results in improved performance compared to individual classifiers, as it leverages the diversity of the constituent models to mitigate errors and enhance overall accuracy.

The comparison conducted in the article reveals that ensemble models generally outperform hybrid models in terms of depression detection accuracy. This superiority can be attributed to the ability of ensemble models to leverage the strengths of multiple classifiers, effectively capturing a more comprehensive range of linguistic patterns associated with depression.

Overall, the findings highlight the effectiveness of automated systems, particularly ensemble models, in aiding the detection of depression through language analysis. By harnessing the power of machine learning and natural language processing, these systems offer a promising avenue for improving the identification and management of depression on a large scale.

***Keywords*—Deep neural networks, depression detection, ensemble methods, sentiment lexicon.**

I. Introduction

Depression, a prevalent mental health condition, has witnessed a rise in cases over the last century due to changes in human lifestyle. Despite this increase, many instances of depression remain undetected [1], underscoring the necessity for automated detection methods. Language usage has emerged as a valuable indicator of depression, with individuals displaying distinct patterns in their linguistic features [2]. Consequently, the development of text classifiers for depression detection has ensued, relying on effective feature representation and analysis.

The study focuses on enhancing the performance of depression detection by examining and comparing two methodologies: hybrid and ensemble learning. Hybrid methods amalgamate symbolic and sub-symbolic artificial intelligence techniques, whereas ensemble methods integrate multiple learning approaches. Through experiments utilizing text classifiers trained on three distinct datasets, the efficacy of these methods is evaluated. The findings indicate that ensemble models surpass hybrid models, showcasing the effectiveness of combining various feature combinations and conducting proper feature selection for accurate depression detection. This research contributes to the field of automated depression detection by implementing hybrid and ensemble methods and emphasizing the significance of feature representation and selection in achieving enhanced performance.

II. Related work

Valuable insights have been gained from research on evaluating textual data and utilizing various NLP techniques to capture users' linguistic tendencies. The automated analysis of the relationship between language and mental states has been achieved through the development of classifier models using a diverse range of feature extraction methods. While some studies have concentrated on statistical approaches for extracting individual features like N-grams [4], linguistic inquiry, and word count (LIWC) [3], and bag of words (BOWs) [6], [7], others have explored the impact of single features in conjunction with different machine learning (ML) approaches.

Recent studies have delved into how combining individual features can enhance classification accuracy, with approaches such as term frequency-inverse document frequency (TF-IDF) + linear discriminant analysis (LDA) and TF-IDF and N-gram + LIWC [8] being explored. Additionally, recent advancements in deep neural networks have been applied to the detection of depression and mental healthcare. For instance, Orabi *et al*. [13] utilized word embeddings to enhance performance in depression detection tasks, comparing convolutional neural network (CNN)-based models with recurrent neural network (RNN)-based models and finding superior performance in CNN-based models. Furthermore, Benton *et al*. [4] investigated the effectiveness of multitask learning (MTL) models on a limited dataset.

In the realm of natural language analysis, a key challenge lies in identifying the relevant set of features. Various methods have been employed to extract pertinent features in text classification literature, including techniques like "bag of phrases," "bag of n-grams," "WordNet-based word generalizations," and "word embedding" methods. Recent studies have emphasized the importance of feature specifications for machine learning (ML) and deep learning (DL) text analysis, enabling the reuse of feature specifications in semantically similar contexts. Misra's review study highlighted different levels of analysis for feature extraction, ranging from words to corpus level, to extract linguistic, semantic, and statistical features from textual data.

Moreover, research on mental state detection techniques has leveraged a variety of features, from linguistic cues and statistical features to user posting patterns, to construct classification models. These features encompass stress-related language use, post timing and frequency, post sentiment, and value contrast, such as shifts between positive and negative sentiments. For example, Stankevich et al. compared the performance of bag-of-words and word embeddings, highlighting the effectiveness of TF-IDF models with morphological features. Shen et al. extracted depression-related linguistic features, while Tsugawa et al. utilized multiple features and topic modeling to predict users' mental states based on their online activity history.

III. Methods

Hybrid Ensemble Learning Approaches for Automated Depression Detection discusses the application of natural language processing (NLP) technologies in solving text classification problems. It highlights the importance of feature extraction at different levels of analysis, such as words, phrases, sentences, and documents, to capture linguistic, semantic, and statistical features from textual data. The section also mentions the shift from rule-based and probabilistic methods to deep learning approaches in NLP, emphasizing the use of models like LSTM and attention-based models for sequential data processing. This model uses three different AIML algorithms to predict the depression detection in females.

A. *Logical Regression*

Logistic Regression is a binary classification algorithm. It models the probability of an input belonging to one of two classes using the logistic (sigmoid) function. The algorithm is trained to minimize the difference between predicted probabilities and actual outcomes. The decision boundary separates the classes, making it useful in various applications such as medicine and finance. It's simple, interpretable, but assumes a linear relationship between features and outcomes. The accuracy of Logical Regression as shown below in fig 1 was around 0.95 and the confusion matrix for logical regression is shown below in fig 2.

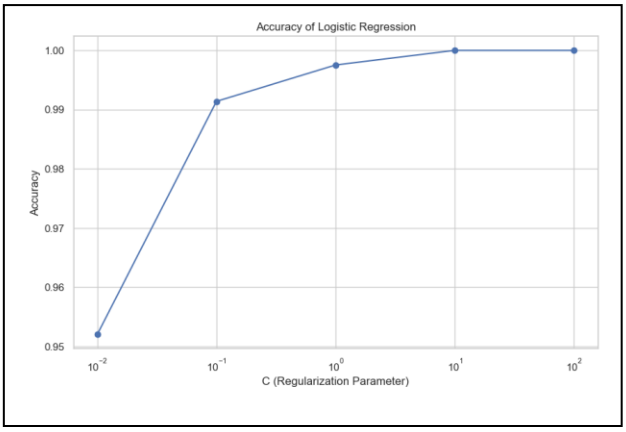

Fig 1. Accuracy of Logical Regression

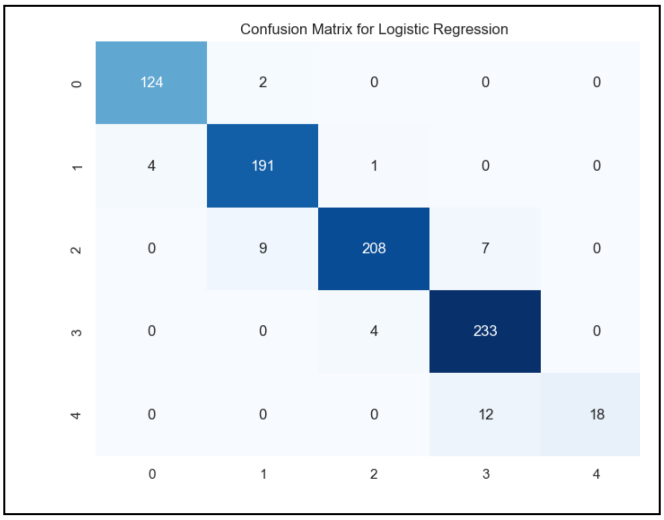

Fig 2. Confusion matrix of Logical Regression

B. KNN

KNN may be a however successful classification calculation. It allots a lesson to an information point based on the larger part lesson of its k closest neighbors within the highlight space. It's instinctive, requires no show preparation, and is appropriate for different assignments like design acknowledgment. In any case, the choice of 'k' is basic, and it can be computationally costly for expansive datasets. The accuracy of KNN algorithm as shown below in fig 3 was around 0.92 and the confusion matrix for KNN algorithm is shown below in fig 4.

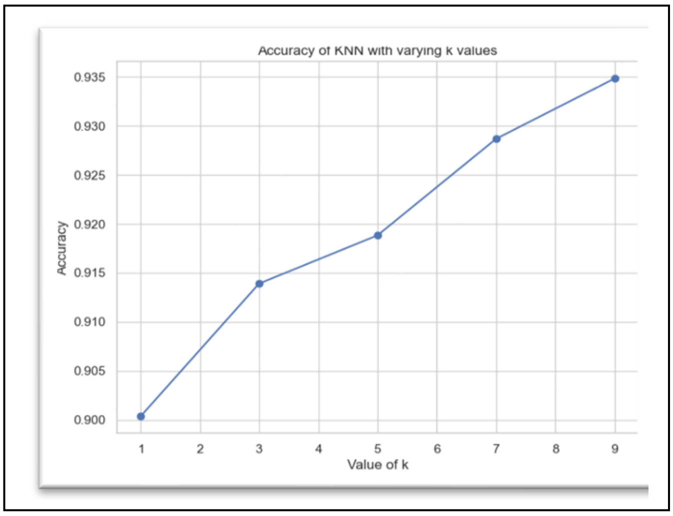

Fig 3. Accuracy of KNN Algorithm

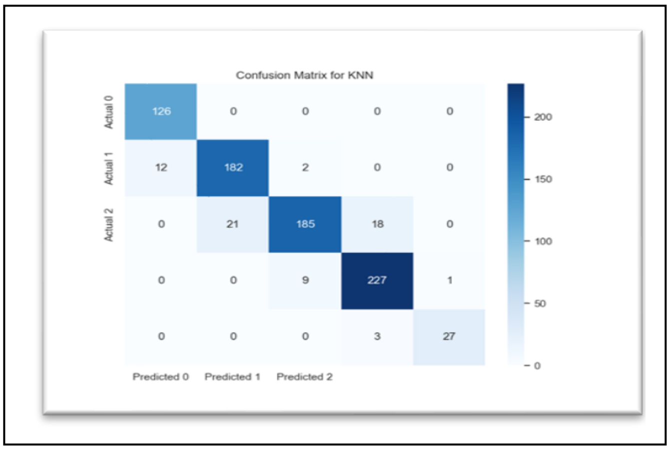

Fig 4. Confusion matrix of KNN Algorithm

C. SVM

SVM is a robust supervised learning algorithm for classification and regression. It finds a hyperplane to separate classes, maximizing the margin. The kernel trick extends its applicability to non-linear data. SVM is effective in high-dimensional spaces, but its performance depends on parameter tuning. Commonly used in image and text classification. The accuracy of SVM algorithm as shown below in fig 5 was around 0.96 and the confusion matrix for SVM algorithm is shown below in fig 6.

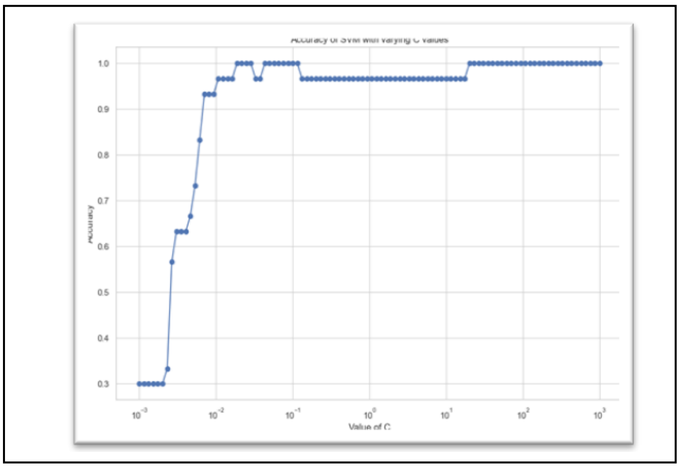

Fig 5. Accuracy of SVM Algorithm

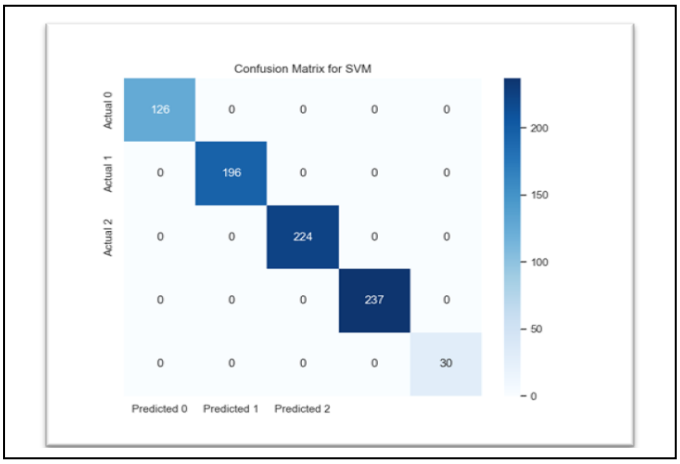

Fig 6. Confusion matrix of SVM Algorithm

IV. EXPERMENT

A. Datasets

A dataset has been compiled from numerous hospitals wherein female patients participated in a survey aimed at assessing their level of depression in correlation with factors such as age, health status, and marital status. This dataset represents real-time information gathered from diverse sources, reflecting the dynamic nature of the demographic and health-related variables under investigation. Through the meticulous aggregation of data from multiple medical institutions, this dataset offers a comprehensive perspective on the prevalence and determinants of depression among female patients across various demographics. The structured collection of this data enables rigorous analysis and exploration of the intricate interplay between socio-demographic characteristics and mental health outcomes, thereby facilitating informed decision-making in clinical and public health settings.

B. Data-Cleaning

The data-cleaning process for the dataset was conducted meticulously to ensure accuracy, consistency, and reliability. Employing statistical techniques and algorithms, inconsistencies, inaccuracies, and missing values were identified and rectified. Outliers and erroneous entries were removed or corrected, and standardization techniques ensured uniformity in data format and scale. Potential biases were addressed to enhance validity. The process involved clearing empty spaces, removing unwanted data, and eliminating IDs associated with zero scores. Notably, the data cleaning was executed on the Jupyter Notebook platform. Adherence to data quality standards underscored the reliability of the cleaned dataset for research and clinical applications.

C. Data Analysis

After the data cleaning procedure, the dataset underwent evaluation, wherein four prominent algorithms were assessed based on insights gleaned from a research paper. These algorithms encompassed Logistic Regression, K-Nearest Neighbors (KNN), Random Forest, and Support Vector Machine (SVM). Distinct sets of scores were derived, one pertaining to responses from 10 inquiries addressing anxiety and the other concerning 6 inquiries relating to overall mental well-being. A composite score, denoted as the average score, was computed by rounding off the mean of these two scores. Subsequently, leveraging this average score, predictions regarding depression levels were made in accordance with pre-established criteria.

TABLE I

Depression Level reference

Total Score	Depression level	Code
1-4	Minimal depression	0
5-9	Mild depression	1
10-14	Moderate depression	2
15-19	Moderately severe depression	3
20-27	Severe depression	4

V. RESULTS

Research in the domain of mental health and text analysis has yielded significant insights into the linguistic patterns of women and their mental well-being. Studies have delved into how linguistic cues, posting behaviors, and sentiment analysis can be harnessed to identify mental health issues, particularly emphasizing features like stress-related language usage, timing of posts, sentiment fluctuations, and linguistic markers indicative of depression. Notably, investigations conducted by De Choudhury et al. [9] and Reece et al. [10] have underscored the potential of leveraging social media data from platforms such as Facebook and Twitter [3] to characterize and predict postpartum depression, as well as anticipate the onset of mental illness in women. Through the analysis of shared data on these platforms, researchers have gained deeper insights into the mental health landscape of women, leading to the development of predictive models aimed at facilitating early intervention and support. The below fig 7. shows the graph for the accuracy of the Ensemble model.

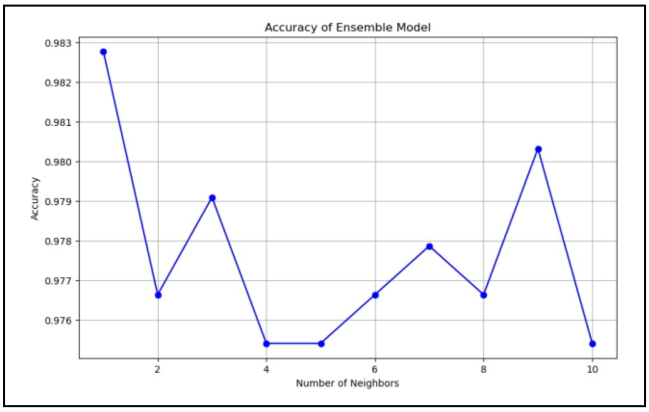

Fig 7. Accuracy of Ensemble Model

Moreover, the amalgamation of natural language processing (NLP) techniques and machine learning methodologies has enabled researchers to explore the linguistic intricacies specific to women's mental health. By extracting features such as linguistic patterns, sentiment analysis, and user posting behavior, studies have constructed classification models capable of accurately detecting mental health issues in women. The adoption of advanced deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has further augmented the efficacy of these models in discerning depression and other mental health ailments in women. By concentrating on the distinct linguistic attributes and online behaviors exhibited by women, researchers are paving the path toward more personalized and efficacious mental health interventions tailored to the unique needs of female individuals. The below fig 8 shows the confusion matrix for the Ensemble model.

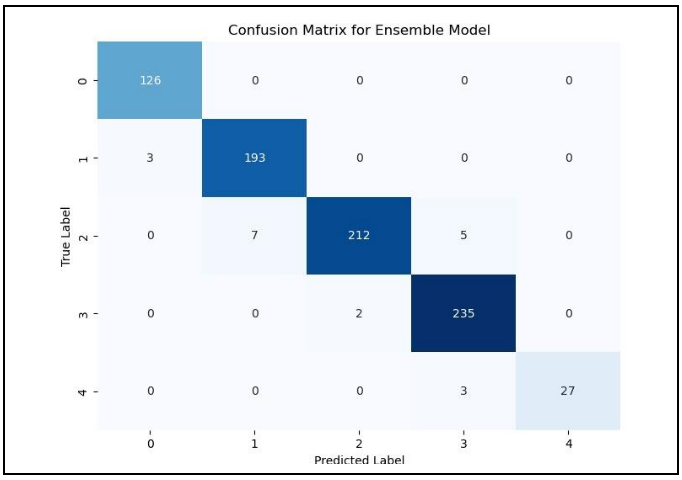

Fig 8. Confusion Matrix of Ensemble Model

VI. Conclusion and Future Directions

In conclusion, inquire about into outfit crossover learning strategies for mechanized sadness discovery has highlighted the viability of coordination common dialect preparing with machine learning models to analyze literary information and anticipate mental wellbeing conditions [10]. Noteworthy advances have been made in creating classification models by leveraging highlights such as phonetic prompts, assumption investigation, and client posting designs, especially in recognizing sadness and other mental wellbeing disarranges. These ponders have emphasized the potential of utilizing social media information from stages like Facebook and Twitter to pick up experiences into individuals' mental states, counting issues such as postpartum misery and the onset of mental illness.

Besides, headways in profound learning designs, such as convolutional neural systems (CNNs) and repetitive neural systems (RNNs) [13], have moved forward the accuracy and adequacy of computerized discouragement location frameworks. Looking ahead, tending to basic challenges such as predisposition, reasonableness, and interpretability in information collection and show preparing forms is basic to invigorate the unwavering quality and moral contemplations of robotized misery location frameworks inside healthcare offices. Furthermore, investigating outfit techniques that combine typical and sub typical counterfeit insights approaches can lead to more strong models for analyzing mental health-related literary information. Future inquiries about ought to moreover look at the effect of social standards and person aberrations on misery location, especially among young people and the elderly populace. By enduring in development and refinement endeavors, analysts can contribute to the advancement of more exact, touchy, and personalized instruments for robotized discouragement location and mental wellbeing back, eventually profiting healthcare conveyance.

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