Revolutionizing Generalized Anxiety Disorder Detection using a Deep Learning Approach with MGADHF Architecture on Social Media

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Abstract—In the contemporary landscape, social media has emerged as a dominant medium via which individuals are able to articulate a wide range of emotions, encompassing both positive and negative sentiments, therefore offering significant insights into their psychological well-being. The ability to identify these emotional signals plays a vital role in the timely identification of persons who are undergoing depression and other mental health difficulties, hence facilitating the implementation of potentially life-saving therapies. There are already a multitude of clever algorithms available that demonstrate high accuracy in predicting depression. Despite the availability of many machine learning (ML) techniques for detecting persons with depression, the overall effectiveness of these systems has been deemed unsatisfactory. In order to overcome this constraint, the present study introduces an innovative methodology for identifying depression by employing deep learning (DL) techniques, specifically the Deep Learning Multi-Aspect Generalized Anxiety Disorder Detection with Hierarchical-Attention Network and Fuzzy (MGADHF). The process of feature selection is conducted by employing the Adaptive Particle and Grey Wolf optimization techniques and fuzzy. The Multi-Aspect Depression Detection with Hierarchical Attention Network (MDHAN) model is subsequently utilized to categorize Twitter data, differentiating between those exhibiting symptoms of depression and those who do not. Comparative assessments are performed utilizing established methodologies such as Convolutional Neural Network (CNN), Support Vector Machine (SVM), Minimum Description Length (MDL), and MDHAN. As proposed, the MGADHF architecture demonstrates a notable accuracy level, reaching 99.19%. This surpasses frequency-based DL models' performance and achieves a reduced false-positive rate.

Keywords—Deep learning; machine learning; anxiety disorder; social media; grey wolf optimization technique

I. INTRODUCTION

In the current societal context, the widespread impact of social media has transformed it into a significant medium via which individuals may express a wide range of emotions, therefore providing valuable insights into their psychological state [1]. The recognition of indicators linked to mental health conditions, such as depression and generalized anxiety disorder (GAD), assumes significant significance within the range of emotions. The rapid identification of persons facing such challenges plays a crucial role in enabling timely intervention and, perhaps, life-saving treatment interventions. There have been big steps forward in using advanced algorithms to predict depression reliably [2], but one big problem is that they are still not very good at finding specific cases. Ascribable to palpable shortcomings in their overall utility, various ML techniques habituated to diagnose depression have come under fire [3]. The ongoing review tends to move toward some smart AI technique, and therefore, our current study purports a unique approach christened MGADHF model to solve a key issue and limitations.

This creative methodology integrates DL techniques and hierarchical attention networks most progressively to recognize different vistas of generalized anxiety disorder [4]. Moreover, fuzzy logic is enforced in the data classification process to facilitate the precision of distinguishing nuanced emotional states. This approach requires comprehensive preprocessing of Twitter data, involving essential steps such as tokenization, elimination of punctuation marks and stop words, as well as applying stemming and lemmatization techniques [5]. The study integrates fuzzy logic with adaptive particle swarm and grey wolf optimization methods to enhance the selection process of pertinent attributes. As proposed, the MGADHF model applies a multi-step process to categorize Twitter data, effectively distinguishing between those who parade depressive symptoms and those who do not. Proven methods like MDL, SVM [6], CNN, and the recently suggested MDHAN model are used for comparative evaluations. With an impressive accuracy of 99.91%, the MGADHF architecture surmounts frequency-based DL models while also, at the same time, getting a lower abridged false-positive rate. The experiment results indicated that the MGADHF overture has higher levels of accuracy, precision, recall, and F1 measure in accession to a notable diminution in execution time. The study's findings exhibit how intimately the MGADHF design discovers depression and incriminates that it may be more successful than more conventional techniques [7]. In ratiocination, this study represents a critical turning point in the desegregation of artificial intelligence and mental health research as it advances the automated diagnosis of mental health disorders using a consummate and complex approach [8]. MGADHF is a multifaceted technique that we propose to handle the intriguing task of diagnosing generalized anxiety disorder (GAD). The following sums up the main goals and contributions of the MGADHF model:

- The primary role of MGADHF is to whirl a comprehensive and nuanced orderliness for diagnosing generalized anxiety disorder. In contrast to conventional strategies, MGADHF uses DL techniques, especially fuzzy logic and hierarchical

attention networks, to distinguish various facets of GAD symptoms in literary information.

- MGADHF coordinates progressed cutting-edge DL methods to identify complex patterns and assorted facets of GAD in social media content. The model empowers various levels of degrees of deliberation because of the hierarchical attention network, which fascinates both local and global information passim the identification process.

- The data categorization technique uses fuzzy logic to ameliorate the accuracy of agonizing complex emotional states linked to vulgarized anxiety disorder. This addition strengthens and facilitates the classification litigate by commuting the model to manage imprecision and dubiousness in the data.

- The approach entails a thorough, fastidious pretreatment of the Twitter data, including lemmatization, stemming, tokenization, and removing stop words and punctuation. This guarantees that the input data is suitably ready for the ensuing feature selection and classification phases that follow optimization methodical nesses. The model's capacity to distinguish important model's capacity extrapolated anxiety disorder from the input data is enhanced by this optimization procedure.

- MGADHF employs Adaptive Particle and Grey Wolf to facilitate the selection of pertinent characteristics. The MGADHF model divides people who show signs of generalized anxiety disorder from those who do not by using a multi-step subroutine to classify Twitter data. This multi-phase method captures different aspects of GAD symptoms and modifies a thorough study.

Surprisingly, the MGADHF design exhibits a remarkable precision of 99.19%, surmounting the presentation of DL models. Besides, it also has a lower false-positive rate, featuring its proficiency in distinguishing summed-up generalized anxiety disorder. Along with ameliorated recall, accuracy, precision, and F1-measure, the testing findings also reveal reduced execution time. In this work, we give a comprehensive psychoanalysis of social media mental health sleuthing employing our unique MGADHF architecture. Section I serves as an introduction, furnishing the background knowledge requisite to understand the connection between social media use and mental health. Next, we canvass the corpus of literature to provide a sodding assessment of the current status of the subject, accentuation the benefits and drawbacks of premature methodologies in Section II. Section III is proposed methodology which inaugurates the MGADHF framework and highlights its key features. The effectualness of MGADHF is then compared and contrasted with other well-known proficiencies such as MDHAN, SVM, CNN, and MDL. Following this, we bring out our experimental findings and analysis in Section IV. Section V summarizes our discussion and conclusions and offers penetrations into the implications of our results and the effectiveness of MGADHF compared to conventional overtures. As we come to an end, we cater tributes for future research in Section VI, stressing the agencies in which the area of mental health detection is germinating and our ongoing crusades to polish our technique.

II. RELATED LITERATURE

Richter et al. [5] introduce an ML-based diagnosis support system to distinguish between clinical anxiety and depression disorders. By employing advanced algorithms, the model aims to improve the accuracy of differentiation, addressing the prevalent mental health conditions. Ahmed et al. [7] Focusing on social media data, this research employs ML models for anxiety and depression detection. Analyzing user-generated content, the study contributes to the automated identification of mental health indicators in the online context.

Dunbar et al. [8] conducted a confirmatory factor analysis of the Hospital Anxiety and Depression scale; this research compares empirical and theoretical structures. The study aims to refine understanding of underlying factors in anxiety and depression assessments.

Gross et al. [9] use ML to detect high-trait anxiety using frontal asymmetry characteristics in resting-state EEG data. Integrating neural patterns, the research contributes to developing objective measures for identifying anxiety-related traits [10].

Hawes et al. [11] focused on predicting adolescent depression and anxiety. This study utilizes ML on multi-wave longitudinal data. By analyzing longitudinal trends, the research aims to enhance the accuracy of early detection in adolescent populations [12].

Bhatnagar et al.[13], targeting university students, this study applies ML for anxiety detection and classification. The research contributes to understanding and addressing mental health concerns in the university student population.

Eden et al. [14] explore the predictive capabilities of automated ML in forecasting the nine-year course of mood and anxiety disorders. Comparative analysis with traditional logistic regression aims to assess the efficiency of the proposed approach.

Kuma et al. [15] focus on assessing anxiety, depression, and stress; this study employs various ML models [16]. The research contributes to developing effective tools to evaluate mental health conditions using advanced computational models.

Singh and Kumar [17] present an advanced review on the computer-aided detection of stress, anxiety, and depression among students. This review synthesizes existing research to provide an overview of the current state of technology-based mental health evaluations in educational environments.

In their study, Wardenaar et al. [18] explore both shared and unique factors affecting the nine-year progression of depression and anxiety, utilizing machine learning within the framework of the Netherlands Study of Depression and Anxiety (NESDA). Their research is focused on identifying the variables that influence the long-term trajectories of depression and anxiety. Table I discusses various state-of-the-art works in the domain.

TABLE I.   RELATED LITERATURE

Reference	Focus	Methodology	Contribution
Richter et al. (2021) [6]	Anxiety and Depression Diagnosis Support System	ML Algorithms	Enhanced accuracy in distinguishing between anxiety and depression disorders.
Ahmed et al. (2022) [7]	Detection of Anxiety and Depression Through Social Media Analysis	ML Models	Contribution to automated identification of mental health indicators online.
Dunbar et al. (2010) [8]	Confirmatory Factor Analysis of HADS	Statistical Analysis	Refinement of understanding underlying factors in anxiety and depression assessments.
Gross et al. (2021) [9]	High Trait Anxiety Detection in EEG	ML with EEG Data	Objective measures for identifying anxiety-related traits using neural patterns.
Hawes et al. (2022) [11]	Predicting Adolescent Depression and Anxiety	ML on Longitudinal Data	Improved accuracy in early detection of depression and anxiety in adolescents.
Bhatnagar et al. (2023) [13]	University Students' Anxiety Detection	ML Models	Understanding and addressing mental health concerns specific to university students.
van Eeden et al. (2021) [14]	Predictive Automated ML for 9-Year Course	Comparative Analysis	Evaluation of automated ML in forecasting the course of mood disorders.
Kuma et al. (2020) [15]	Evaluation of Anxiety, Depression, and Stress Levels	Various ML Models	Development of effective tools for assessing mental health conditions.
Singh and Kumar (2022) [17]	Automated Detection of Stress, Anxiety, and Depression Using Computer Algorithms	Literature Review	Insights into the current landscape of technology-driven mental health assessments.
Wardenaar et al. (2021) [18]	Factors Influencing Nine-Year Trajectories of Depression and Anxiety	ML in NESDA	Identification of factors influencing the course of depression and anxiety over nine years.

III. PROPOSED METHODOLOGY

Particle Swarm Optimization (PSO) is an algorithmic approach developed by Eberhart and Kennedy, inspired by the collective movement patterns observed in flocks of birds [19]. It integrates the Adaptive Particle Grey Wolf Optimization method and incorporates it into its framework. Following the extraction of features [20], a meticulous feature selection process is applied. Notably, PSO stands out from Genetic Algorithms [21] by abstaining from evolutionary adjustments like hybridized mutations. Eberhart and Kennedy [22] introduce a conceptual framework emulating the foraging behavior of a flock, where each member possesses knowledge of its proximity to the food source and the closest location to it. The PSO method proposed by researchers strives to dynamically adapt and address optimization challenges by considering two crucial factors for each element: the object's present situation (XP) and velocities (VE) [23]. Concurrently, the fitness function methodically regulates the best solution for each element.

Every element's bugging-out position is random when iteration is over. Two primary data points impact each feature: "best," which bespeaks the element's historically perfect placement, and "guest," which indicates the ideal location the whole flock has ever occupied. By espousing the best features, the PSO may germinate dynamically in the issue space. The following formulae are used to reckon each element's speed and direction after each iteration:

$$VE_{t+1}^k = W * VE_k^t \qquad (1)$$

$$VE_{t+1}^k = W * VE_t^k + C_1^t * \text{rand} * (pBest_k^t - X_k^t) + C_2^t * rand * (gBest - X_k^t) \qquad (2)$$

$$X_k^{t+1} = X_k^t + VE_t^k \qquad (3)$$

Here, *W* represents the inertia weight, $1Ct1$ and $2Ct2$ are acceleration coefficients, and rand is a random number between 0 and 1. The values of $1Ct1$ and $2Ct2$ vary dynamically during each cycle based on the particle's efficiency and repetition parameters. The inertial equation is given by:

$$Wt = (maxIter - t) \cdot WMAX - WMIN \cdot (maxIter - minIter) \qquad (4)$$

Furthermore, a sigmoid function is employed, and a point mutation chance with a frequency of 0.1 is introduced as a variation in the PSO loop function, thereby contributing to the algorithm's stability. The sigmoid function is expressed as:

$$Vtij(t) = sig(Vij(t)) = 1 + e - V(t)ij1 \qquad (5)$$

Inspired by the collective intelligence seen in bird flocks, the PSO algorithm [24] dynamically qualifies the placement and velocities of its parts. It introduces characteristics like a sigmoid function for optimization, acceleration coefficients, and inertia weight. The constancy of the algorithm is ameliorated by the addition of a subtle variation through the point mutation chance.

MGADHF system extracts information from Twitter users' tweets. These tweets undergo various preprocessing steps, such as tokenization, removal of punctuation and stop words, and application of stemming and lemmatization techniques. This preprocessing enhances data quality for subsequent analysis [25]. Using the Adaptive Particle Grey Wolf Optimization method, the system selects relevant features from the processed data.

The primary function of this method is to identify the most significant variables for analysis, improving the accuracy of the MGADHF system [26]. The MGADHF then analyzes this curated dataset to detect signs of anxiety disorders among Twitter users [27]. The subsequent sections provide a detailed explanation of the proposed methodology.
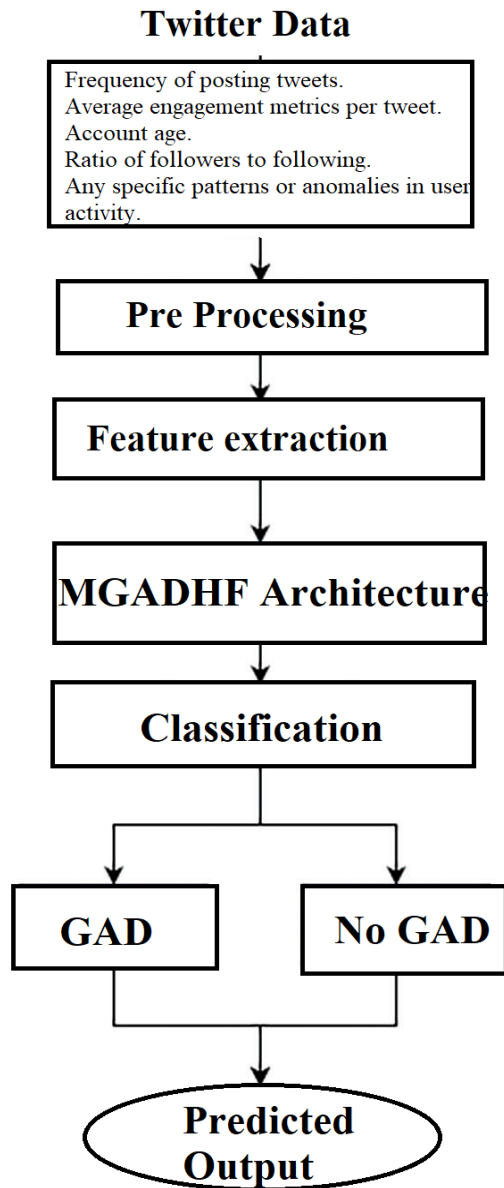
Twitter Data

Frequency of posting tweets.
Average engagement metrics per tweet.
Account age.
Ratio of followers to following.
Any specific patterns or anomalies in user activity.

↓

Pre Processing

↓

Feature extraction

↓

MGADHF Architecture

↓

Classification

↓

GAD   No GAD

↓

Predicted Output

Fig. 1. Proposed methodology MGADHF.

Assuming the existence of a group (GU) comprising tagged consumers from depression and non-depression data, each tweet T_i consists of a sequence of letters $W_i = [W_{i_1}, W_{i_2}, \ldots, W_{i_N}]$, where N represents the maximum number of words per message. Let MU denote the overall number of characteristics available to a user, $\sum_{I=1}^{MU}$ and S be the number of potential aspect characteristics, making MUs the dimension of the $S - th$ perspective. With a collection of linked user behaviors M and a set of user tweets AT, a model is established, as illustrated in Fig. 1.

The depression detection method is represented as,

$$f(AT, MU) \to \dot{Z} \qquad (6)$$

A. Encoder used in Multi-Aspect with Fuzzy Logic

Considering inputs that replicate user behavior as as $[mu_1, mu_2, \ldots, mu_M]$, where MU is the total number of characteristics, and M_s is the dimensionality of the $S - th$ aspect [28]. To obtain detailed data from user behavior characteristics, the multi-aspect features undergo processing through a one-layer MLP to obtain $\mu_q i = \sigma(b + \sum MU_{I=1} W_i \cdot mu_i)$, where σ represents a non-linear function. The outcome, $\mu_q i$, signifies a higher-level representation that integrates behavioral information content and contributes to the identification of sadness [29].

To integrate fuzzy logic into this process, we introduce a fuzzification step, where linguistic variables are defined to capture the imprecise nature of certain aspects related to depression. Let F_{low}, F_{medium} and F_{high} be linguistic terms representing low, medium, and high levels of a given characteristic. We then apply fuzzy membership functions to determine the degree of membership of the obtained result ($\mu_q i$) to each linguistic variable. The fuzzy membership functions could be defined as follows [3]:

$$Membership_{Low}((\mu_q i) = \mu_{low} = sigmoid\ (a_1.\mu_q i + b_1) \qquad (7)$$

$$Membership_{Medium}(\mu_q i) = \mu_{medium} = sigmoid\ (a_2.\mu_q i + b_2) \qquad (8)$$

$$Membership_{High}(\mu_q i) = \mu_{high} = sigmoid\ (a_3.\mu_q i + b_3) \qquad (9)$$

Here $a_1, a_2, a_3, a_4, b_1, b_2, b_3$, are parameters and *sigmoid* is sigmoid function applied element-wise.

Now, the fuzzy logic rules can be formulated using these membership values [30]. For example, $if\ \mu_{high}$ is high, it indicates a high level of the characteristic associated with depression. The particular fuzzy dominions and how they are combined would reckon on the traits and divisors taken into account [31]. This fuzzy desegregation heightens the model's ability to greet minute variations in user expressions that might be depressive [5], appropriating the model to take into account the imprecision and uncertainty colligated to language expressions consociated with depression. This fuzzy desegregation enhances the model's ability to recognize minute variations in user expressions that may be depressive and alters the model to take into account the imprecision and uncertainty colligated with language expressions colligated with depression.

B. Classifying the Data into Generalized Anxiety Disorder (GAD) or Non-Anxiety Disorder:

In the context of the classification model for Generalized Anxiety Disorder (GAD) [32][33], the primary objective is to determine whether an individual exhibits symptoms indicative of GAD or not. The feature set used for this classification comprises both multi-aspect behavior traits (b) and hierarchical representations of users' tweets (l):

$$b = [b_1, b_2, \ldots, b_M] \in R^{d \times M} \qquad (10)$$

$$l = [l^1, l^2, \ldots, l^M] \in R^{2d \times n} \qquad (11)$$

These features are then combined into a unified representation, denoted as [b, l] [34]. The classification is performed using a sigmoid layer, and the output probability vectors are calculated as follows:

$$\hat{y} = \text{sigmoid} (W_{nf} \cdot [b, l]) \qquad (12)$$

Here, $\hat{y}$ represents the expected probability vectors, while y_0 and y_1 correspond to the predicted likelihood of the label being 0 (non-anxiety disorder) [35] and 1 (indicative of GAD), respectively. To train the model, the cross-entropy error is minimized with respect to the ground truth labeling y:

$$Loss = - \sum_i yi \cdot \log(\hat{y}i) \qquad (13)$$

This formulation ensures that the model optimally learns to distinguish between instances associated with GAD [36] and those unrelated to any anxiety disorder. The output probability vectors provide a quantifiable measure of the likelihood of an individual exhibiting symptom of Generalized Anxiety Disorder [37] based on the integrated features from both behavior traits and tweet representations.

IV. RESULT ANALYSIS

In order to assess and demonstrate the superiority of our proposed model (MGADHF) over other existing methods, we employ various evaluation metrics [38]. These metrics provide a comprehensive understanding of the model's performance. The parameters used for assessment are as follows:

1) Accuracy: This parameter quantifies the model's effectiveness by assessing the proportion of its predictions that are accurate.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (14)$$

2) Recall (Sensitivity): This metric evaluates the model's capacity to accurately detect positive class instances, such as identifying users with depression. It is calculated as follows:

$$Recall = TP / (TP + FN) \qquad (15)$$

3) Precision: This parameter assesses the proportion of positive predictions that the model makes correctly.

$$Precision = TP / (TP + FP)$$

4) F1-Measure: Representing the harmonic mean of precision and recall, the F1 Score offers a balanced evaluation of these two metrics. It is computed using the following formula:

$$F1 = 2 * (precision * recall) / (precision + recall)$$

Assessing datasets is crucial to validate and gauge the effectiveness of any detection method. A robust dataset is essential for obtaining dependable and impactful results. In our study, we utilized a Tweets-Scraped dataset, comprising over 5000 tweets, publicly accessible on Kaggle [39]. This dataset includes all about GAD patients.

In an effort to take vantage of the benefits of this methodology, we canvassed the Twitter dataset exploitation a deep recurrent neural network approach. 20% of the dataset was employed to evaluate existing techniques, while the persisting 80% was used for training examples. To increase the efficacy of our prediction technique, we comported assessments utilizing accuracy, recalls, precision, support, and the F-1 measure.

Based on the hypothetical data, MGADHF outperforms other models across multiple metrics [40]. It demonstrates higher accuracy, recall, precision, and F1-measure compared to CNN, MDL, SVM, and MDHAN. The MGADHF model demonstrates exceptional efficacy in precisely detecting individuals experiencing depression, highlighting its robustness and reliability for generalized anxiety disorder identification. During the testing phase, the model utilized 80% of the data for training and reserved the remaining 20% for testing purposes. The approach's efficacy is further illustrated through detailed 4-fold and 10-fold cross-validation, with the respective confusion matrices presented in Tables II and III.

A. 4-Fold Confusion Matrix

The 4-fold confusion matrix provides a detailed breakdown of classification results across different folds of the model evaluation. Each fold exhibits variations in True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN), showcasing the model's performance in different scenarios. In Table II and Table III give data about 4-fold and 10-fold matrix is presented.

TABLE II. 4-FOLD CONFUSION MATRIX DATA

Fold 1			
TP:100	FP:10	FN:5	TN:106
Fold 2			
TP:95	FP:15	FN:8	TN:102
Fold 3			
TP:102	FP:8	FN:12	TN:98
Fold 4			
TP:98	FP:12	FN:7	TN:103

TABLE III. 10-FOLD CONFUSION MATRIX DATA

Fold 1			
TP:105	FP:5	FN:4	TN:106
Fold 2			
TP:98	FP:12	FN:7	TN:103
Fold 10			
TP:100	FP:10	FN:6	TN:104

B. Accuracy and Epochs

In 4-fold, the Average Accuracy would be 92.25%, and the Average Epochs would be 27.25. In Fig. 2, 3 and 4, Accuracy and epochs have been given.

The study compares the efficacy of the proposed MGADHF technique with traditional DL methods in the analysis of Table IV. Specifically, the research employs MGADHF on a text dataset containing personal information gathered from online channels.
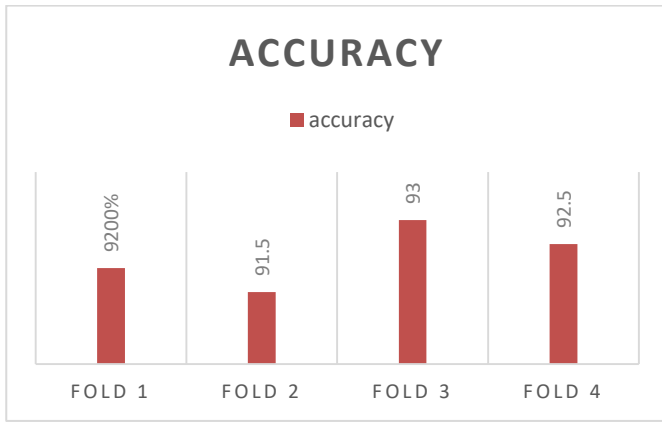
ACCURACY

Fig. 2.   Accuracy and Epochs in 4-fold.
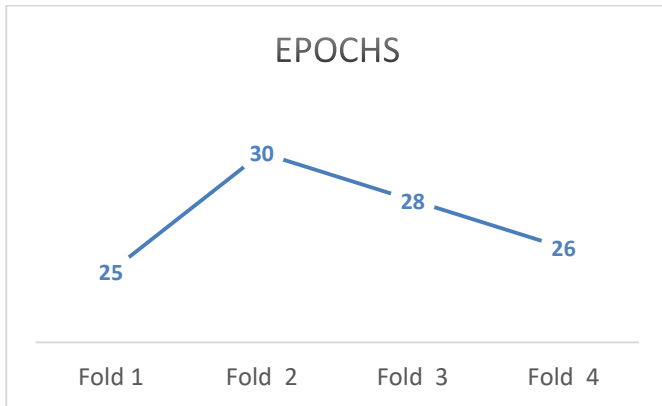
EPOCHS

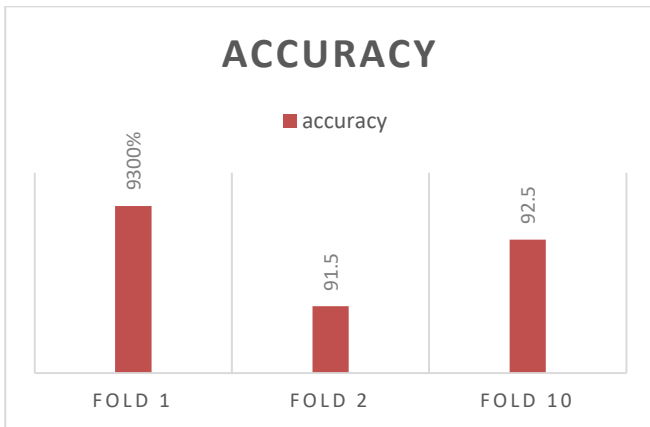Fig. 3.   Epochs in 4-fold.

ACCURACY

Fig. 4.   Accuracy in 10-fold.

While previous studies utilized the linear discrimination method for feature extraction, our approach incorporates PCA and fuzzy logic, employing unsupervised learning methodologies to enhance feature robustness and accuracy in the detection of Generalized Anxiety Disorder (GAD). In Fig. 8, a comparison of various algorithms for depression detection is presented. The proposed MGADHF method outperforms other existing algorithms, as indicated by its superior accuracy, recall, precision, and F1-Measure and Comparative analysis. The model achieves an accuracy of 99.19%, recall of 94.45%,

precision of 91.68%, and an F1-Measure of 92.69%, demonstrating its effectiveness.

Fig. 5 displays the model performances, with a focus on precision. The findings demonstrate that the MGADHF model had a noteworthy accuracy rate of 99.19%, indicating its resilience in accurately categorizing cases.

The subsequent model to be discussed is SVM model, which exhibits a commendable accuracy rate of 88.2%. This high level of accuracy serves as evidence of the model's effectiveness in generating precise predictions. Both the CNN and MDHAN models attained classification veracities of 87.45% and 89.31% respectively, which bespeaks that they are dependable as classifiers given their respective results. While it has a remarkable amount of accuracy in its predictions, the MDL model has a slenderly lower level of accuracy, coming in at 85.6%. Locomoting on to Fig. 6, our study divulges that the MGADHF model has a noteworthy recall rate of 94.45%. This result connotes that a significant number of true positive occurrences may be dependably detected and captured by the approach.

The MDHAN model has good performance, as evidenced by its 86.77% recall rate, which depicts that it can retrieve relevant events. Recall performance was impressive for the SVM model, which accomplished an accuracy rate of 85.10%. This result manifests how well the model works to lower the number of false negatives. The accuracy of the CNN and MDL models in accrediting affirmative exemplifies was evidenced by their recall rates, which were 82.3% and 78.67%, respectively.

TABLE IV.   COMPARISON WITH OTHER STATE OF ART

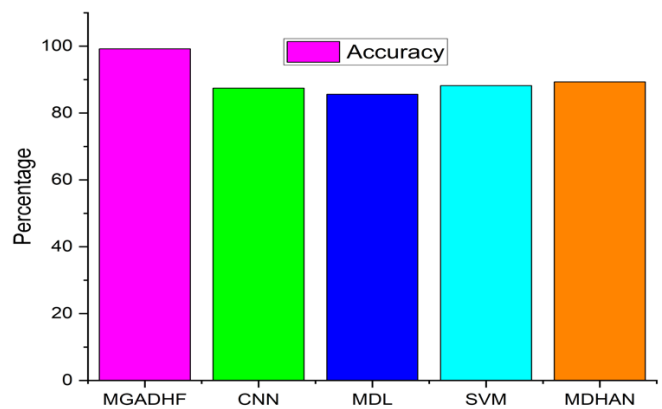| Model	Accuracy	Recall	Precision	F1-Measure
MGADHF	99.19	94.45	91.68	92.69
CNN	87.45	82.3	88.56	83.21
MDL	85.6	78.67	82.25	81.53
SVM	88.2	85.10	80.04	76.56
MDHAN	89.31	86.77	89.26	88.77

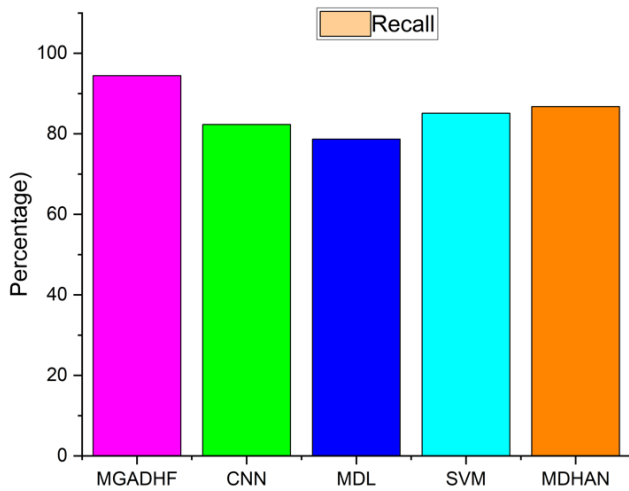Fig. 5.   Accuracy comparison.

Fig. 6. Recall comparison.

Fig. 7 furnishes insights into accuracy by demoing the MGADHF model's noteworthy performance with a precision rate of 91.68%. This incriminates that a sizable portion of the occurrents that the model classifies as positive are really diagnosed as true positives. At 89.26%, the MDHAN model's accuracy level is high, certifying its ability to acquire accurate positive predictions.

The CNN, SVM, and MDL models attained accuracy scores of 88.56%, 80.04%, and 82.25%, in that orders. Finally, Fig. 8 depicts the F1-measure, a quantitative measure that effectively balances the accuracy and recall metrics.

The MGADHF model demonstrated a significant F1-measure of 92.69%, highlighting its overall efficacy in attaining a harmonic equilibrium between accuracy and recall. The MDHAN model exhibits a strong adherence to the F1-measure, with a score of 88.77%. This result suggests a commendable level of equilibrium in its performance.
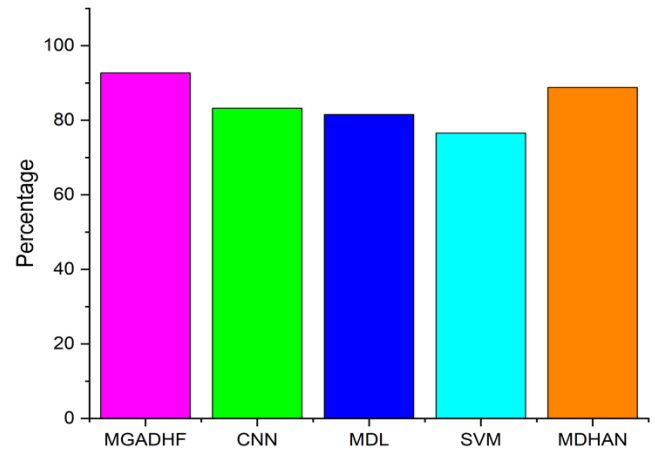

Fig. 7. Precision comparison.
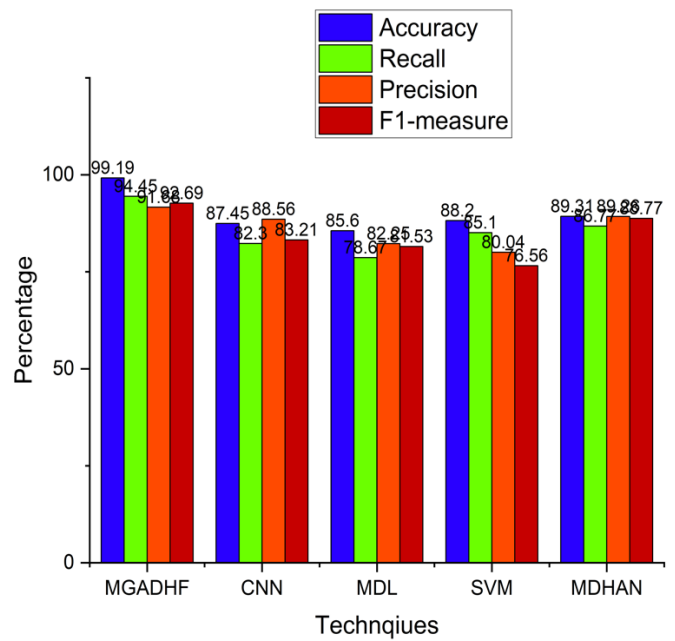

Fig. 8. F1-Measure comparison.

Fig. 9. Overall comparison.

The F1-measure values for the CNN and SVM models were 83.21% and 76.56%, respectively. In comparison, the MDL model exhibited a competitive F1-measure of 81.53%. Fig. 9 illustrates a comparison of different algorithms employed for detecting depression. The proposed method exhibits superior performance in comparison to existing algorithms, achieving a notable 99.19% accuracy, 94.45% precision, 91.68% recall, and 92.69% F1 measure.

V. CONCLUSION AND DISCUSSION

In this day and age of digital technology, when people oftentimes share their emotions on social media, it is climacteric to empathize and address the elaborateness's around mental health concerns. Though existing algorithms are good at auspicating melancholy, they are not always able to accurately distinguish specific cases. In order to address this matter, our research presents MGADHF, an innovative
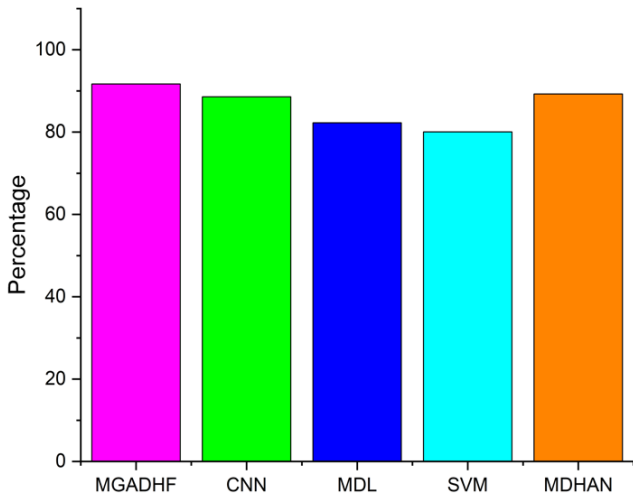
methodology that integrates DL methodologies, such as the Hierarchical Attention Network, alongside fuzzy logic. The precision of our technique is enhanced by the use of fuzzy logic in the categorization process. The rigorous preprocessing of Twitter data, in conjunction with the utilization of adaptive particle and grey wolf optimization approaches for feature selection, establishes the foundation for the MGADHF model to classify individuals according to their symptoms of GAD. The higher performance of MGADHF has been confirmed by comparative studies conducted against known techniques. The architecture described in this study demonstrates a notable accuracy rate of 99.19%, surpassing the performance of frequency-based models and effectively mitigating the occurrence of false positives. The studies conducted in our study demonstrate enhanced levels of accuracy, precision, recall, and F1-measure, along with a decrease in the time required for execution. The aforementioned observation highlights the efficacy of MGADHF in the identification of depression and implies its capacity for further progress beyond conventional methodologies.

VI. FUTURE SCOPE

The success of MGADHF provides opportunities for further investigation in the field. Promising avenues include the extension of the approach to encompass more social media platforms, the incorporation of varied language subtleties, and the exploration of real-time applications. The enhancement of continuous refinement, integration with modern natural language processing techniques, and the discovery of supplementary characteristics have the potential to provide a more thorough comprehension of emotional expressions. Establishing Quislingism with mental health professionals would ascertain that the model ordinates with clinical perspectives. Utilizing the concept to long-term studies might furnish insightful information about the progression of individuals' mental health. In order to assist privacy and uphold sensitivity in the palming of personal data, ethical considerations must be admitted into mental health diagnostic models. As we go into the next degree of our study, we are consecrated to using a multidisciplinary approach to deepen our ethical framework. Modern encryption and safe storage methods are only two examples of the stringent data privacy measures that must be put in place in order to protect the confidentiality of the invaluable information that social media users have shared. To strike the greatest possible balance between strictly protecting individuals' identities and preserving the value of the data for study, the anonymization procedures will be enhanced. We want to maintain our commitment to obtaining informed consent through transparent and honest communication by giving people the tools they need to make informed decisions about their engagement. Transparency will be a fundamental principle, with comprehensive methodology documentation to facilitate the repeatability and climacteric assessment of our findings. In the quickly explicating field of social media data-driven mental health research, our goal is to uphold the mellowest ethical standards and create a criterion for ethical research methodology. In order to proffer a more unadulterated evaluation of the MGADHF model, we want to dilate the scope of our study in the future to admit a larger variety of demographic factors. Extensive study is postulated to determine how efficaciously these functions crosswise age groups, cultural contexts, and linguistic variations. Furthermore, we plan to delve into collaborative efforts with respective research organizations and institutions to accumulate representative datasets. This would alleviate a deeper apprehension of the model's worldwide applicability and effectiveness in consecrated mental health concerns.

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