Check for updates

Explainable Deep Attention Active Learning for Sentimental Analytics of Mental Disorder

USMAN AHMED, Western Norway University of Applied Sciences, Norway
RUTVIJ H. JHAVERI, Pandit Deendayal Energy University, India
GAUTAM SRIVASTAVA, Brandon University, Canada and China Medical University, Taiwan
JERRY CHUN-WEI LIN*, Western Norway University of Applied Sciences, Norway

With the increasing use of online mediums, Internet-delivered psychological treatments (IDPs) are becoming an essential tool for improving mental disorders. Online-based health therapies can help a large segment of the population with little resource investment. The task is greatly complicated by the overlapping emotions for specific mental health. Early adoption of a deep learning system presented severe difficulties, including ethical and legal considerations that contributed to a lack of trust. Modern models required highly interpretable, intuitive explanations that humans could understand. To achieve this, we present a deep attention model based on fuzzy classification that uses the linguistic features of patient texts to build emotional lexicons. In medical applications, a diversified dataset generates work. Active learning techniques are used to extend fuzzy rules and the learned dataset gradually. From this, the model can gain a reduction in labeling efforts in mental health applications. In this way, difficulties such as the amount of vocabulary per class, method of generation, the source of data, and the baseline for human performance level can be solved. Moreover, this work illustrates fuzzy explainability by using weighted terms. The proposed method incorporates a subset of unstructured data into the set for training and uses a similarity-based approach. The approach then updates the model training using the new training points in the subsequent cycle of the active learning mechanism. The cycle is repeated until the optimal solution is found. At this point, all unlabeled text is converted into the set for training. The experimental results show that the emotion-based enhancement improves test accuracy and helps develop quality criteria. In the blind test, the bidirectional LSTM architecture with an attention mechanism and fuzzy classification achieved an F1 score of 0.89.

Additional Key Words and Phrases: Sentiment detection, mental healthy analysis, Internet-delivered interventions, adaptive treatments, NLP

1 INTRODUCTION

Artificial Intelligence in Medicine (AIM) has the potential to improve the practice of medicine by enabling physicians as well as other medical professionals to analyze various data more naturally as well as accurately [33]. Remote healthcare entered the era of the Internet of things (IoT) applications. Tracking as well as analyzing healthcare content helps to facilitate the adoption of high-quality healthcare services. Assessing patients' health with IoT devices is a need of time as well as it plays a vital role in managing health conditions. Biomedical devices can help improve the informatics research community to solve complex healthcare and improve human health.

*Corresponding author.
Authors' addresses: Usman Ahmed, Western Norway University of Applied Sciences, Bergen, Norway, usman.ahmed@hvl.no; Rutvij H. Jhaveri, Pandit Deendayal Energy University, Gandhinagar, India, rutvij.jhaveri@sot.pdpu.ac.in; Gautam Srivastava, Brandon University, Brandon, Canada, SRIVASTAVAG@brandonu.ca and China Medical University, Taichung, Taiwan; Jerry Chun-Wei Lin*, Western Norway University of Applied Sciences, Bergen, Norway, jerrylin@ieee.org.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
© 2022 Association for Computing Machinery.
2375-4699/2022/7-ART $15.00
https://doi.org/10.1145/3551890

Just Accepted

Modern data-driven technologies can help clinicians interpret large volumes of diverse medical data as well as make accurate diagnoses, as well as treatment decisions for patients [17].

With the advent of the COVID-19, research on the Internet-delivered healthcare facility was carried out commercially. The research idea is to monitor healthcare without direct contact with physicians. Thus, this helps the pandemic situation and reduces the loaded health facilities. This tends to increase mobile healthcare requirements that require real-time systems to assist the physician during the mobile healthcare solutions. Artificial intelligence (Artificial Intelligence) tools are helping as well as may be able to reduce physician workload during the current pandemic [20]. Artificial Intelligence attempts to replicate human behaviors using labeled data (ML) through machine learning. AIM is integrated with the electronic health record (EHR) system used by the majority of healthcare organizations worldwide [8]. Data collected by EHR systems enable the development of more practical Artificial Intelligence applications. In general, an electronic health record includes both structured and unstructured data (e.g., patient demographics, diagnoses, and procedures) and unstructured data (e.g., physician notes and clinical reports). This makes it challenging to interpret EHR-based data because it is inconsistent.

There are several data science applications for fuzzy-based systems, including human reasoning and decision models. By combining cooperative fuzzy principles with system intelligence, fuzzy modeling can contribute to the understanding of Artificial Intelligence decisions, specifically in the area of explainability as well as interpretability for the accuracy performance of machine learning models. By combining machine learning and fuzzy modeling approaches, researchers have begun to address the challenge of making artificial intelligence models explainable to humans. The goal of Artificial Intelligence systems is to maximize accuracy while providing users with interpretable conclusions and results. Artificial Intelligence systems can be optimized for better performance with various unstructured data available. However, fuzzy-based systems retain their fundamental nature of comprehensible intelligibility. They can enhance the performance of Artificial Intelligence models and help construct explainable artificial intelligence for humans.

There are several data science applications for fuzzy-based systems, including human reasoning and decision models. By combining cooperative fuzzy principles with system intelligence, fuzzy modeling can contribute to the understanding of Artificial Intelligence decisions, specifically in the area of explainability as well as interpretability for the accuracy performance of machine learning models. By combining machine learning and fuzzy modeling approaches, researchers have begun to address the challenge of making artificial intelligence models explainable to humans. The goal of Artificial Intelligence systems is to maximize accuracy while providing users with interpretable conclusions and results. Artificial Intelligence systems can be optimized for better performance with various unstructured data available. However, fuzzy-based systems retain their fundamental nature of comprehensible intelligibility. They can enhance the performance of Artificial Intelligence models and help construct explainable artificial intelligence for humans.

1.1 Motivation

The COVID-19 epidemic that has hit the world in the last two years has also contributed to an increase in mental health-related difficulties. According to WHO[1], ninety-three % of the world's nations have seen an increase in the number of people struggling with mental health issues. People are experiencing a higher physiological stress component as a result of the lockdown, which includes fears of illness in addition to uncertainty about the future of humanity [37]. A much higher emotional stress rate has occurred as a direct result of factors such as social isolation, lack of interaction opportunities, uncertainty in education, and unpredictable work schedules. Fear of illness, lack of protective equipment, social disconnection, and working in a stressful atmosphere have been associated with increased incidence of anxiety and depression among healthcare workers. According to [18], the

[1]shorturl.at/enwTV

Just Accepted

overall rate of depression that occurred during the pandemic is much higher than anyone could have expected. People are able to communicate with each other through a variety of online forums and social media platforms as the globe moves towards the implementation of online systems in more and more areas [23]. Due to the epidemic, people in our global society have become accustomed to communicating with each other online [26]. The ability to test for depression online can be useful in identifying those who are at high risk for developing mental health problems. If used at the right time, it can help improve overall health [28].

1.2 Contribution

The goal of this effort is to detect depressive symptoms based on the writings written by the patients. Our method uses a fuzzy classification model to achieve higher precision. A strategy based on deep concentration has been included in the proposed framework, which allows for detecting and visualizing signs of depression. In the practice of a clinical psychiatrist, the patient will talk to the doctor or use some kind of online approach to discussing their psychological problems (especially in today's world). To isolate the components of depression, we first classify the emotional components of the text as symptoms related to depression. Our fuzzy categorization technique assists psychiatrists and other medical professionals to interpret data more effectively by using fuzzy principles. The framework serves as a decision support system as it integrates an attention-based deep learning embedding, an entropy-based data labeling, and an interpretable fuzzy model. The relationship between observed depressive symptoms and mental health can be better understood using our online interactive tool (ICT). We experimented with different architectural layouts for the attention mechanism and then combined these layouts with fuzzy rules to improve the explanation depending on the frequency of attention words. This work directly addresses the issue of interpretability of a deep learning model by integrating a fuzzy classifier into the deep learning scheme and using learned embeddings as input features to the fuzzy classifier. To briefly summarize the contributions, we have the following:

(1) For mental health data to develop a low-dimensional continuous representation, we propose a fuzzy lexicon set of semantic vectors for synonymous expansion.
(2) We have shown that the fuzzy lexicon knowledge expansion helps to improve model accuracy for the attention-based embedding approach.
(3) Empirical evaluation of the proposed model and comparison with state-of-the-art methods.

2 RELATED WORK

Many works, as well as studies, have been developed recently, making use of NLP-based methodologies in computer-aided systems. We provide a summary of the related literature in this section.

Despite the fact that AIM research efforts were promising, interpretability issues prevented clinical use. The lack of confidence that medical professionals have in AIM has been demonstrated in a number of studies [10]. Significant causes of trust issues include recognized limitations on access to medical data, a lack of expertise needed to integrate clinical workflows, regulatory limitations, and development and deployment hurdles that AIM systems have experienced internationally. The Defense Advanced Research Projects Agency (DARPA) announced its Explainable Artificial Intelligence (XAI) research program in 2017 [13]. According to DARPA, modern artificial intelligence systems have limitations in terms of interpretation and communication. This is because humans cannot understand how Artificial Intelligence systems work, i.e., why Artificial Intelligence can be able to make a particular strategy and decision.

Researchers also argue that physicians can easily rely on pharmaceuticals like aspirin, despite actually understanding the drugs' interaction mechanisms fully [39]. If an Artificial Intelligence system started explaining the decision-making by compromising performance, would physicians accept that system? On the other hand, drug regulatory authorities ensure that any drug undergoes a rigorously designed, randomized clinical trial before

Just Accepted

being permitted for public use (COVID-19 Vaccines as a recent example). Additionally, regulatory agencies also perform post-marketing surveillance, such as the Food and Drug Administration in the United States of America (USA). The FDA's primary purpose for pharmaceuticals is to quickly withdraw drugs from the market in case of unexpected side effects, fatality being the worst of these. Artificial Intelligence systems built under limited datasets may have potential biases due to generalization issues in new samples. Therefore, Artificial Intelligence systems do not have a similar mechanism to take full responsibility for safety issues and efficacy. XAI can help to understand whether AIM decisions are valid and get consensus from medical experts. XAI promotes trust in AIM by acting as a decision support system [15]. Explainability plays a vital role in supporting the implementation of Artificial Intelligence in clinical decision-making [15, 38].

Languages with low resources use expansion. As a result, lexical and synonymic gaps may occur [32]. The expansion method was used in the development of Assamese WordNet. As a result, there is no synonymy. WordNets can be thought of as a network of several words connected by semantic similarity. Link prediction techniques were used to estimate the number of missing synonyms in the Assamese WordNet. It has been shown that local strategies, based on proximity and not too sophisticated, are more effective than global models, which are complicated and use network embedding. Some of the terms found are not synonyms. Nevertheless, they are conceptually related to the target phrase and can be called semantic cohorts.

When studying public opinion on an event, one of the most important tasks is to analyze the opinions expressed in short texts. Due to the significant effort involved in manual labeling, categorizing opinion targets is often considered a low-supervision task. Using a weakly supervised Event Graph Convolution Network (EventGCN), Xiang *et al.* addressed the categorization of opinion targets in microblog comments [41]. The model presented an event graph with three typical event microblogs, including the co-occurrence relationship of event keywords from microblogs, the response relationship of comments, and the similarity of documents. The event graph also included the typical similarity of documents. It is possible to provide a correct representation of both word properties and comment properties to finish the categorization using a small number of labels as a guide. The results of the experiments conducted on two different datasets of event microblogs show that EventGCN performs much better than the current classification techniques.

Emotion classification in texts is an important technique for natural language. A fuzzy system is an effective tool for processing imprecise input and can be used for sentiment analysis [12]. This research provides a new interpretation of a multi-task fuzzy system for text sentiment classification [12]. A fuzzy clustering approach is used to retrieve both the standard (public) information for each task. Clustering centers can be used to obtain the parameters of fuzzy systems. With the obtained parameters, a multi-task learning system is designed to learn the following parameters. The created fuzzy rules are the correlation information between tasks and the independent information of each task. The experimental results on many text sentiment datasets confirm the validity of the model.

Another paper presents an aspect-based text analysis algorithm for Hindi. The proposed method not only evaluates the overall attitude of a sentence but also assigns different moods to the different constituents of a sentence. Bornali *et al.* deals that Hindi Dependency Parser (HDP) is used to detect the association between an attribute word (using Hindi SentiWordNet) and is based on the premise that closely related words indicate a sentiment towards a particular aspect [34]. The system computes the overall polarity of the phrase by assigning the sentiment to an aspect with the shortest distance between them and constructing a dependency graph. The system achieves 83.2 percent accuracy on a corpus of movie ratings and its results are compared with baselines and current efforts. According to the results, the proposed method can be used in future applications such as social media analysis.

With the recent advances in online social networking (OSN), the services are finding more and more applications in daily life. On the other hand, online social networks are seeing an increasing number of cases of cyberbullying, a relatively new form of harassment that occurs via Internet-based technological devices. As a result, researchers

Just Accepted

are interested in studying the behaviors of cyberbullying. According to various studies, cyberbullying can have a devastating impact on mental health, especially among adolescents. Various machine learning approaches are being used, and much research has been done to curb or potentially put an end to cyberbullying. On the other hand, traditional detection methods still have problems, such as low accuracy. Therefore, it is crucial for the natural language processing and machine learning communities to find a detection solution that is both effective and efficient. In this particular research project, the features of cyberbullying are first broken down and studied from lexical and syntactic perspectives. Then, a new detection technique derived from FastText and various word similarity schemes [40] is proposed. Experiments are then conducted to evaluate the efficiency and effectiveness of the proposed approach. The results show that the developed method has the potential to effectively increase both the detection accuracy and the recall rate of cyberbullying.

Fine-grained sentiment analysis and the purpose of aspect-level sentiment analysis is to determine the sentiment polarity of a particular opinion target that has been conveyed. The vast majority of currently available studies examine how knowledge about the target can be used more effectively in modeling the sentence, rather than using information describing the interaction between the sentence and the target. In this article, we argue that predicting the polarity of an aspect's emotion level depends not only on the context but also on the target. First, we provide a novel model based on LSTM and the attention mechanism to predict the mood of each target within the review. This model is called a matrix-interactive attention network and models both the target and the context [36]. The model uses an attention matrix to learn the interactive attention of both the context and the target, and it also creates the final representations of both the target and the context. Then, we develop a deep interactive memory network by introducing two gate networks based on the proposed model. This network is designed to capture numerous interactions between the target and context. The deep interactive memory network can exceptionally formulate a specific memory for different targets, which is essential for sentiment analysis.

Providing a high-quality media monitoring service presents both a new opportunity and a new difficulty in the face of the growing amount of text in the news and the development of artificial intelligence. We realize an application to improve media monitoring reports by mining large news texts with a semantic analysis approach based on Latent Dirichlet Allocation (LDA) and Apriori algorithm. The method uses natural language processing and text mining techniques for this purpose. First, the strategy proposes the use of an LDA model to identify topic phrases of news texts while reducing the dimensionality of the news. In the next step, it proposes to use the Apriori algorithm to determine how topic terms are related. The final step is to determine the meaning of the topic words in the message text and graphically represent the intensity and interdependence between the topic terms. This program can extract the news topics and identify the correlation and interdependence between the news topics in the news text. It can also extract the message topics. The results show that the approach based on LDA and Apriori can help the media monitoring managers to better understand the information hidden in the news texts and produce a better media analysis report.

The analysis of a user's state of mind, e.g., regarding a product, message, or other topics, can be greatly enhanced by recognizing emotions in natural languages. However, due to the subjective nature of emotions and the limited and ambiguous boundaries surrounding them, it is challenging to extract relevant aspects from a flood of raw social texts. Different people interpret and use different terms to talk about the same subjective attributes. An Internet of Things-based system for classifying sentiments expressed in tweets using a combination of the Term Frequency Inverse Document Frequency (TF-IDF) algorithm and a deep learning model [16]. First, the unprocessed tweets go through a filtering process called tokenization. This helps extract essential attributes while removing irrelevant or noisy data. In the second step of the process, the relevance of features is estimated both locally and globally using the TF-IDF statistical method. Third, the Adaptive Synthetic (ADASYN) class balancing approach is applied to correct the problem of unbalanced classes among different emotion classes. Finally, a dynamic epoch curve-based deep learning model was developed to predict emotional states. The proposed approach is evaluated with two separate datasets of Twitter sentiments. Dynamic epoch curves show

Just Accepted

the behavior of test and training data. This approach has been shown to be superior to widely used methods that are considered state-of-the-art models.

In another study, a special dataset called "Cardiac-200" was used in addition to the standard dataset called "PhysioNet". PhysioNet includes 1500 samples of acoustic heartbeat events (without augmentation) and 1, 950 samples of acoustic heartbeat events (with augmentation) [30]. A cardiac dataset designed to balance normal and pathological acoustic heartbeat events. An average of 10-12 acoustic heartbeat events. The acoustic heartbeat events studied use audio processing to extract additional information from the recorded sound signals of the heartbeat. Noise robust acoustic heartbeat images are classified using LSTM-CNN, RNN, LSTM, Bi-LSTM, CNN, K-means clustering, and SVM. The InfusedHeart framework outperformed several specialized machine learning and deep learning techniques. The learning framework has an accuracy of 89.36% (without augmentation) and 93.386% (with augmentation), with a standard deviation of 10.64 and 6.62 (with augmentation), respectively.

Cloud computing has transformed traditional healthcare systems into competent healthcare systems (SHC). SHC improves health care management through wearable devices and connectivity to quickly retrieve information [5]. Wearable gadgets contain many sensors for motion detection. Unlabeled sensor data is formed on cloud servers, which requires a lot of storage and processing. A federated learning-based human motion identification method is proposed to solve the limitations of SHC. Automatic labelling of unlabeled data using Deep Learning. The data is then learned using federated learning (FL), where edge servers communicate only parameters to the cloud, but not sensor data. The BiLSTM is used to classify SHC data.

Luong *et al.* argue for both local as well as global attention [24]. Their paradigm of global attention is a synthesis of soft and hard attention. The model takes advantage of batch-based attention, which contributes to rapid convergence. The local attention model takes advantage of prediction-based attention. Both local, as well as global attention, can be efficiently computed. However, it requires domain knowledge and diverse data instances for tuning the architecture, which is not a trivial task and inefficient.

While deep neural architecture can achieve better scalability that helps achieve domain generalization, these models cannot capture data subjectively, uncertainty, as well as human-like reasoning [22]. As shown in [9], fuzzy modeling can help capture trust as well as human-like reasoning. This research aims to show how fuzzy inference can be used in conjunction with Deep Learning to index network properties as a measure of trust. The task of indexing properties is subjective and introduces an element of ambiguity. It requires adaptive learning that cannot be achieved by sequentially stacking different modules.

Table 1. Critical analysis of the methods.

Paper	Data-set-Method	Machine learning	Adaptive learning	Performance
[42]	Online Feature based	Decision Tree	No	54.5
[1]	Erisk 17/18 - Embedding	One class SVM and KNN	No	77
[3]	Amazon Mechanical Turk - Synonyms	Attention network	No	88.8
Proposed	Amazon Mechanical Turk- Word Embeddings	Fuzzy attention learning	Yes	89

Using the texts [1, 3, 42], Table 1 presents ways to detect depression associated with mental illness. These methods have led to the technique being included in a number of databases, including `eRisk 2017/2018`, `Twitter`, and `Reddit`. Nevertheless, semi-supervised learning remains a viable option for improving the model. This research demonstrates that fuzzy lexicons can be helpful in training approaches and attempts to expand the trainable circumstances with a semantic enhancement strategy. Moreover, the study shows that fuzzy lexicons can help in semantic expansion. The data annotation effort is something that the proposed methodology hopes to reduce. Thus, the method contributes to the generalization of the learning system. The semantic vectors are categorized using information from the lexicon, which is derived from the context in which they are found. The

Just Accepted

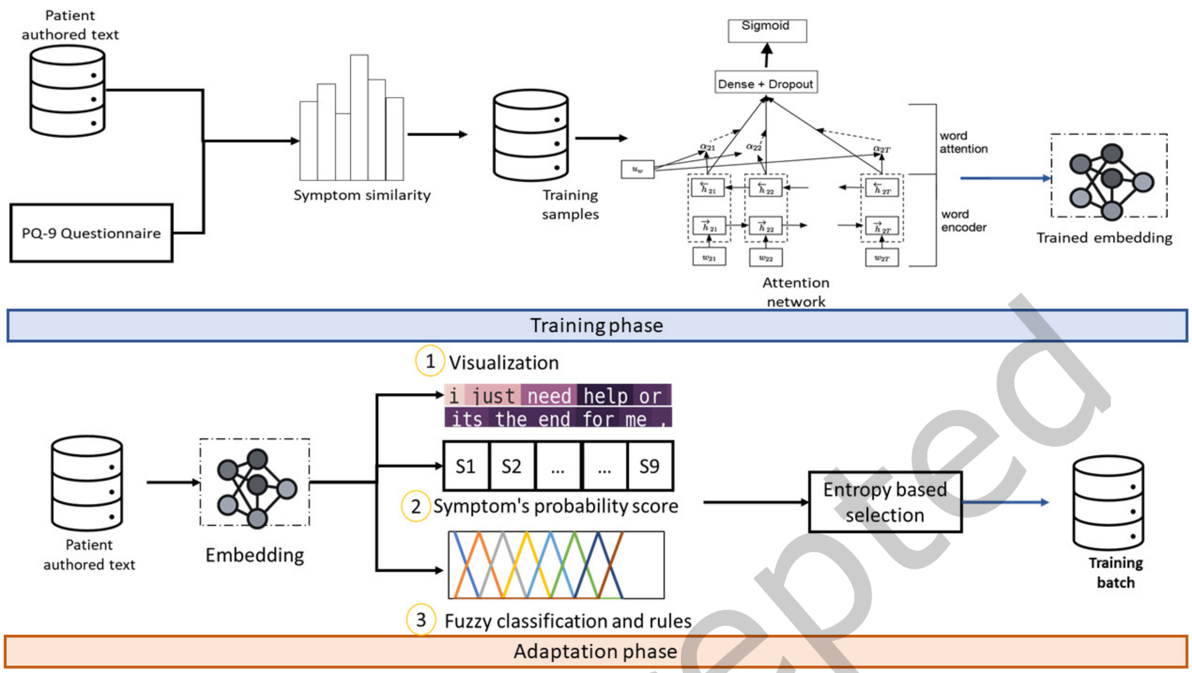

Fig. 1. Attention-based domain adaptation is used to create a flow of training and adaptation. The visualization, symptoms' probability score, fuzzy classification and triggered rules are suggested to the psychiatrists that will be provided to the patient for certain symptoms.

resulting word embedding selects a subset of the unlabeled text based on the semantic information. The approach integrates the newly discovered training points into the overall training of the model.

3 LEXICON EXPANSION USING FUZZY WEIGHTED ATTENTION NETWORK

This article proposes an embedding strategy to detect depressive symptoms both quickly and effectively. As shown in Fig. 1 and 2, symptom scores are calculated using cosine similarity. Lexicons are created using extensive knowledge and word embedding. In this study, the lexicon method was modified by applying cosine similarity to the PHQ-9 symptom score. A strategy known as trained lexical enrichment was presented to increase the level of expertise and incorporate word size for similarity. The training method proposed to extract depressive symptoms from the text written by a patient alone is discussed in Section 3.4. The adaptation phase is discussed in Section 3.7 with Fig. 2. Below is an example of the composed text of a patient (an anonymous user). The processed data of the example is shown in Fig. 3.

> *Hello, long-time depression sufferer here. I'm just having a hard day today as well as figuring out why I am even fighting this battle. No one cares about me etc. Why keep fighting this fight? I think I should give up and let the depression win so I can pass on and be at peace in heaven.*

In mental health, classification according to the ICD10 [29] is complicated. The dynamic nature of emotional symptoms has different degrees as well as natures concerning patients. As a result, treatment of specific disease processes requires different methodologies to handle complex problems, i.e., depression and anxiety. The assessment process includes mental health issues obtained by listening to the patient's queries. Psychiatrists and

Just Accepted

other medical professionals extract valuable elements to assess the clinical features of patients. For diagnosis, the psychiatrist uses a conventional technique that involves questionnaire-based analysis, such as the PHQ 9[2]. The survey helps determine diagnostic accuracy and reliability of the clinical circumstances of the person experiencing symptoms. The questionnaire includes a section on the types of symptoms and their frequency of occurrence. The total score is then used to diagnose mental disorders according to a predetermined cut-off point. The results of the questionnaire help classify the behavior as mild, moderate, or severe. This technique is called Clinical Symptom Elicitation Process (CSEP) [29].

This research aims to improve the explainability of the process by using fuzzy categorization based on a deep attention network. Active learning is used to improve adaptability. Each symptom group is labeled based on the frequency of patient messages.

3.1 Psychometric questionnaires (PQ)

For the collection of patient reports, the method considered here uses the well-established Patient Health Questionnaire-9 (PHQ-9) questionnaire [21]. The PHQ-9 is commonly used to measure symptoms of depression. The PHQ-9 method can help identify nine different behavioural patterns included in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM V)[3]. As indicated in Table 2 as well as in a sample document[4], these nine symptoms are then categorized as problems with sleep, interest, concentration, as well as eating problems. After completing the evaluation of the questionnaire, the psychiatrist creates the rating score. The rating score is intended to reflect the patient's level of depression. To assess the effectiveness of the therapy, the PHQ-9 was administered to the patient to measure the severity of the patient's depression. Some alternatives are available, such as the PHQ-2, which consists of two items, and the PHQ-15, which consists of fifteen somatic PHQ symptoms. Screening and diagnosing mental health problems using the ICD10 criteria can be a difficult undertaking [29]. Questions about each category are asked by the psychiatrist, who then evaluates the patient's responses to determine the relative frequency of each category as follows:

a) score 3: nearly every day.
b) score 2: more than half the days,
c) score 1: several days,
d) score 0: not at all,

3.2 Seed term generation

In this work, seed terms can be extracted directly from PHQ 9 questionnaires. Any lexicon can be built making use of symptoms of depression given as common resources for psychiatrists, as given in Table 2. In this work, we made use of Wordnet [25] for the extraction of first-order antonyms, hypernyms, as well as hyponyms. From Wordnet, every word from a given category may possess different synsets that can be used to express unique concepts. Synsets can be categorized both into semantic as well as lexicon-based relations. In many other works, the use of various lists for symptoms of depression in a variety of systems for classification is presented [27]. The practical systems for classification given for depression, for example, DSM[5], as well as the International Statistical Classification of Diseases and Related Health Problems 10 (ICD 10) [29] are well known and can be used widely to assess depression scales that have since been merged [27].

The seed term in this study was derived from the PHQ 9 questionnaire. The vocabulary was created using symptoms of depression from widely available resources for psychiatrists, as shown in Table 2. We extracted

[2]https://www.mdcalc.com/phq-9-patient-health-questionnaire-9
[3]https://www.psychiatry.org/psychiatrists/practice/dsm
[4]https://www.uspreventiveservicestaskforce.org/Home/GetFileByID/218
[5]https://www.psychiatry.org/psychiatrists/practice/dsm

Just Accepted

the first order of hypernyms, hyponyms, as well as antonyms in this study using Wordnet [25]. Each category in Wordnet has its collection of synsets used to convey specific terms. The synsets are classified according to their semantic as well as lexical relationships. Other research has used a variety of different lists of symptoms of depression classified according to different systems for classification [27]. Major systems for the classification of depression such as the DSM[6] as well as the International Classification of Diseases and Related Health Problems 10 (ICD 10) [29] are widely used depression scales that have been merged to create an excellent essential list of symptoms [27].

3.3 Preprocessing

One of the most important steps in the process of text processing is preprocessing. Any text written by a patient is analyzed according to the following method:

(1) Every text is tagged with the UTF-8 encoding convention and then processed and formatted according to this standard. This ensures
(2) Change all capital letters in each word to the appropriate lowercase letters.
(3) Remove any tabs or spaces that appear between the text. Convert each word to its lowercase equivalent.
(4) Eliminate unique characters that have no meaning. (#, +, -, *, =, HTTP, HTTPS).
(5) Convert text-based terms to complete words, e.g., *can't* by cannot and so on.

3.4 Word embedding using emotional lexicon

Knowledge-based emotion embedding, also known as EKB, uses a word sense lexicon in addition to several learned contextual embeddings. Using a pre-training method for the global vector for word representation (GLOVE) [31], we computed word embeddings for each word used in the written texts of inpatients. The dimensions used were 300. Then, our model was trained using embedding for hyper-tuning and domain adaptation. It is necessary to extend the glove embedding since it was trained on data from the generic structural language. In order to incorporate word sense, transfer learning is used as the method of choice. This is due to the fact that most of the embedding is done with open source data, especially *Wikipedia texts*, and sentiment knowledge, also *Twitter data*, is taught. The explanation is as follows: sentiments are denoted by both the expressions *sad* and *happy*, so the two concepts are not mutually exclusive. On the other hand, each of these expressions expresses a unique mental state. For this reason, it is important to extend the embedding using the sense of the word. In this study, we extracted target terms from a part of speech, namely (*noun*, *verb*, *adverb*, as well as *adjective*). We used the corpus T, which consists of the text collection $T = \{d_1, d_2, \dots, d_n\}$, as well as the *WordNet* used to extract synonyms, antonyms, and hypernyms, as well as physical meaning for each as well as every extracted part of speech. This increased the number of emotional words in the provided word list $W = \{w_1, w_2, \dots, w_K\}$. In this way, we develop the emotional lexicon. Then, the vocabulary is created from the set W used to train the model.

In this study, we retrieved target phrases from one part of speech, namely *noun*, *verb*, *adverb*, as well as *adjective*. We used the corpus T, which consists of the text collection $T = \{d_1, d_2, \dots, d_n\}$, and the *WordNet*, which was used to extract synonyms, antonyms, and hypernyms, as well as the physical meaning for each extracted part of speech. For this reason, there were more words expressing emotions in the supplied word list $W = \{w_1, w_2, \dots, w_K\}$. As a result of this process, the emotional lexicon is created. Then, the set W that was used to train the model is used to create the vocabulary. The resulting embedding is the learned vector X, which can be written as $X = \{x_1, x_2, \dots, x_m\} \in \mathbb{R}^{m \times \delta}$, where $delta$ is the dimension of the vector. The sentence embedding can be calculated by taking the average of the word vectors found in the patient author's text. Using the information provided by the text author, the trained model is applied to the patient data to convert it into a vector and nine

[6]https://www.psychiatry.org/psychiatrists/practice/dsm

Just Accepted

Table 2. PHQ-9 questionnaire and seed terms of each and every symptom.

Symptoms	PHQ 9	Seed terms
S1	Little interest or pleasure in doing things	interest
S2	felling down depressed or hopeless	feeling , depressed , hopeless
S3	trouble feeling or staying asleep or sleeping too much	sleep, asleep
S4	feeling tired or having little energy	tired, energy
S5	poor appetite or over eating	appetite, overeating
S6	feeling bad about yourself or that you are a failure or have let yourself or your family down	failure, family
S7	trouble concentrating on things such as reading the newspaper or watching television	concentration, reading , watching
S8	moving or speaking so slowly that other people could have noticed or the opposite being or restless that you have been moving around a lot more than usual	moving, speaking, restless
S9	thoughts that you would be better off dead or of hurt yourself	dead, hurt , suicide

symptoms. To compare the two matched embeddings, the cosine similarity method is used. For each of the nine symptoms, we have a similarity value that ranges from 0 to 1.

The vector X represents the text written by the patient, while the vector Y represents the symptom lexicon. V is used to construct semantically aware vectors from textual features. The similarity between the two embeddings indicates that the published text is strongly associated with specific symptoms, as shown in Fig. 1.

3.5 Dataset

In this particular study, we classified the nine different symptoms using a dataset compiled from a variety of Internet forums and websites [27]. In our method, an entropy-based technique is used to expand the scope of the acquired knowledge and to ensure that rare occurrences do not affect the functioning of the proposed system. The PHQ-9 rating scale was used for commenting. According to this scale, a score of 0 indicates no depression, 1 indicates mild depression, 2 indicates moderate depression, and 3 indicates severe depression. [27]. We change the annotation to a binary class for each symptom, where 0 represents the absence of symptoms and 1 represents the presence of symptoms. Table 3 contains a comprehensive breakdown of each step in the data collection process.

Table 3. The statistical summary of the training and testing set.

Type	Statistics
Corpus size (# of posts collected)	15044
# of sentences	133,524
Avg. sentences per post	8.87
Avg. words per post	232
set for training size (# of posts)	14,944
Testing set size (# of posts)	100

3.6 Deep learning model

We used a feed-forward neural network as a baseline for comparison in the study. For this, the glove embedding method is used to extract the tokens from the text. The average method is used so that we can get an approximate idea of the length of the comments. The model is composed of hidden layers $(30, 20, 10)$ that are activated using the ReLU function for activation [6]. Our objective is to be able to classify nine unique symptoms using several labels. The last layer has the nine-unit sigmoid function. The function for loss is the cross-entropy function.

The tests used a recurrent neural network (RNN) with a generalized recurrent unit (GRU), and the data showed that LSTM cells performed very well as an RNN architecture in the sequential task. By using the LSTM architecture unidirectionally, it is possible to transport a final time step of the hidden state to the output layer. In addition, we used a bidirectional LSTM architecture that sequentially receives input token lists and sets a single parameter for the forward rolled LSTM. As a result, the position of each token now has two input states that combine to

Just Accepted

determine the output state. This leads to an increase in the attention layer, which is reflected in both the following equation and the hierarchical model proposed by Yang et al. [43]. The dropout ratio is adjusted at 0 : 5 to prevent overfitting and regulate the LSTM layer.

$$\boldsymbol{i}_t = \sigma\left(\boldsymbol{x}_t\boldsymbol{W}^{(i)} + \boldsymbol{h}_{t-1}\boldsymbol{U}^{(i)}\right) \tag{1}$$

$$\boldsymbol{f}_t = \sigma\left(\boldsymbol{x}_t\boldsymbol{W}^{(f)} + \boldsymbol{h}_{t-1}\boldsymbol{U}^{(f)}\right) \tag{2}$$

$$\boldsymbol{o}_t = \sigma\left(\boldsymbol{x}_t\boldsymbol{W}^{(o)} + \boldsymbol{h}_{t-1}\boldsymbol{U}^{(o)}\right) \tag{3}$$

$$\tilde{\boldsymbol{c}}_t = \tanh\left(\boldsymbol{x}_t\boldsymbol{W}^{(o)} + \boldsymbol{h}_{t-1}\boldsymbol{U}^{(o)}\right) \tag{4}$$

$$\boldsymbol{c}_t = \boldsymbol{f}_t \circ \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \circ \tilde{\boldsymbol{c}}_t \tag{5}$$

$$\boldsymbol{h}_t = \boldsymbol{o}_t \circ \tanh\left(\boldsymbol{c}_t\right) \tag{6}$$

In addition, the developed framework had a mechanism for using the term "important" in the text [43]. We replaced the LSTM layer with the attention approach. This structure helps in extracting descriptive terms for classification problems. The dropout layer is provided with the attention output vector as input. The formal representation of the network is explained below. Training large networks using supervised learning traditionally requires a large dataset of labelled data. The greatest need, as well as the dependency of the application, is on the labeled data. When training a supervised model, the dataset generated by an active learning model proves to be the most informative. In cases where there is an abundance of data that cannot be categorized manually, active learning is used. In this work, similarity-based features were used to intelligently label a tiny amount of data, and then the entire dataset was trained using an entropy-based instance selection method. The entropy process of instance selection is used to expand the limited number of instances and to select the data distribution [14]. This process contributes to the progressive expansion of knowledge over time.

Nevertheless, the framework as designed is adapted from attention methods that can be used in the utilization of the importance of words in text[43]. An attention method was added instead of using a generic LSTM layer. This change/add-on may assist in extracting words that are informative in classification tasks. We feed the output vector from the attention method as input into the dropout layer. We give a more formal definition as well as a description next. More traditionally, supervised learning needs a sizeable labelled dataset for training in any extensive network. The primary dependency of the application is the labeled data. The relevant data is generated and is the primary responsibility of the active learning model. We only keep the data with the highest predictive nature for training the model. When the data from the applications are too big to manually label, we can use an active learning model. A similarity-based feature process is smartly used to label data in this work. Afterwards, the entropy-based selection is used for training on the entire dataset. We adopt an entropy-based selection methodology for the expansion of the lower number of instances as well as to choose the data distribution. The entire process assists in expanding knowledge as time progresses.

$$\boldsymbol{v}_t = \tanh\left(\boldsymbol{h}_t\boldsymbol{W}_a + \boldsymbol{b}_a\right) \tag{7}$$

$$s_t = \boldsymbol{v}_t\boldsymbol{u}_a^\top \tag{8}$$

$$\alpha_t = \frac{\exp\left(s_t\right)}{\sum_{t=1}^{T}\exp\left(s_t\right)} \tag{9}$$

$$\tilde{\boldsymbol{h}} = \sum_{t=1}^{T}\alpha_t\boldsymbol{h}_t \tag{10}$$

Just Accepted

Algorithm 1 Fuzzy classification using attention weighted network

Input: attention-weighted lexicons.
Output: fuzzy classification rules.
1: $Lexicons \leftarrow Lexicon(attention_network)$;
2: $Sets \leftarrow Fuzzy_{set}(Lexicons)$;
3: **Fuzzification:** Fuzzify the weighted words;
4: **Fuzzy Rules generation:** Generate rules based on the class and weights;
5: **Defuzzification:** Convert rules to fuzzy output;
6: Apply inference;
7: Validate data;
8: Visualized fuzzy weighted attention network;
9: **Return:** fuzzy inference model.

In Algorithm 1, the operation procedure is described in detail. Starting from a trained model and embedding (Algorithm 1, input), we then extract lexicons using a trained attention network (Algorithm 1, line 1). Vector representations are obtained using the emotion lexicon and then integrated with the lexical set and the attention network (Algorithm 1, lines 1-2). It was decided to insert the lexical set (Algorithm 1, line 2) into the text. The normalized vector can then be obtained using the pool layer, explained in more detail in the Sections 3.4, 3.7, 3.7.1, 3.7.2, as well as in Fig. 2 (Algorithm 1, lines 3-8). Then, a small set of sentences with an average embedding is selected, and the similarity between the sentences is calculated (Algorithm 1, line 8) to derive the labels of the sentences. After that, the gradient is updated and inference is used as the result (Algorithm 1, line 10).

3.7 Fuzzy modeling

The Classification Based on Associations (CBA) approach is used in this research to develop rules for the classification problem [11]. Firstly, the objectives of the fuzzy controller are shown in Fig. 2, which is the output of the produced text trained based on the user interaction with the online system. Based on the CBA, a fuzzy set is selected. Mamdani framework is used for the text classification part which is based on the output of the deep attention method [35]. The rule-based classification helps to determine the reasons for the prediction of the attention network and the explainability of words. Physical intuition is used for the fuzzy objective to construct the fuzzy rules based on fuzzy input. This part required deep expertise.

3.7.1 Fuzzifier model. In fuzzification, the input is the frequency of the attention words used for the prediction. This word frequency is used as input. The value of the crisp input is determined by a membership function, and the membership function is also responsible for producing the value of the fuzzy output in the form of a degree. Looking at each and every word frequency, it can be mapped to order paired documents or degree of goodness [35].

$$Triangle(x; a, b, c) = \begin{cases} 0, & x \leq a \\ \frac{X-a,}{b-a} & a \leq x \leq b. \\ \frac{c-x,}{c-b} & b \leq x \leq c. \\ 0, & c \leq x. \end{cases} \tag{11}$$

We used a triangular fuzzy system that takes the frequency of individual words as input and outputs a triangular fuzzy system based on this information. In this paper, we used a triangular membership function. We have a different formulation that we developed by combining the *min* as well as *max*, we have an alternative expression for Eqs. 11 as well as 12.

Just Accepted

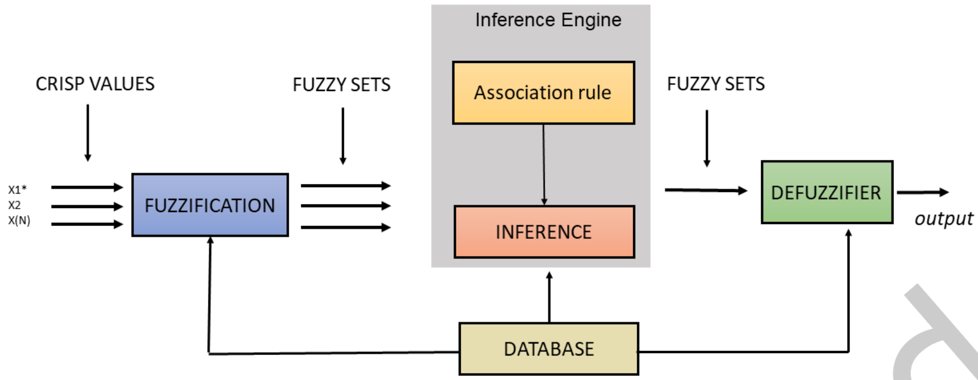

Fig. 2. A workflow of the designed fuzzy model (Mamdani framework).

$$Triangle(\mathrm{x}; a, b, c) = \max\left(\min\left(\frac{x-a, c-x}{b-a} c-b\right), 0\right) \tag{12}$$

3.7.2 Fuzzifier parameters. The inference engine is responsible for converting fuzzy data into rules. The result is then sent to a defuzzifier, which takes a fuzzy input and produces another fuzzy output based on that input. We used a method called CBA, which stands for Classification Based on Associations, to categorize the fuzzy rules and create rules [11]. It starts with discovering the common element groups that contribute to the construction of support and confidence. Then, the rules are arranged in a certain way to create a classifier.

3.7.3 Defuzzifier model. In this particular research paper, we used the approach known as center average de fuzzifier [35]. The formula for defuzzifying the mean is found in Eq. 12, where y^{-i} denotes the mean of the region μ_0^i (small, medium, large, etc.) and M is the total number of rules included in the rule base. The result is assigned to nine symptoms included in Table 2 based on the word frequency association performed.

3.7.4 Fuzzy training. After the word frequency is determined using the attention approach, the fuzzification process is performed, the categorization of the fuzzy rules is determined using the CBA, and the defuzzifier helps to convert fuzzy sets and fuzzy rules. The prediction is based on a comparison of the calculated membership value with previous membership values found on the computer, with a threshold value between +0.001 and −0.001. The output results can then be calculated using the Centroid averaging technique. The result is entered into the database at the same time the rule is updated.

3.7.5 Fuzzy prediction. It may be explained using the following steps:

(1) Determine what a fuzzy set is using the triangular membership function of word frequency retrieved using the attention approach.
(2) Generate fuzzy rules using association rule mining.
(3) Calculate and set a membership score for each rule in the system.
(4) Calculate the membership value of the set used for training and base your prediction on the threshold of this value.

3.7.6 Output. The method added to the local attention model in this study is between soft and hard attention. The basic idea is to first detect an attention point or position within the input sequence and choose a window around that position to build a local model of soft attention [3]. A predictive function (predictive alignment)

Just Accepted

learns the position within the input sequence. In our case, the nine represents the output layer (each class per symptom). The dense layer has the soft activation used for probability prediction (vector of probabilities). The probability indicates how likely it is that the instance will have each of the above symptoms. In this study, the argmax function is used to convert the predicted probabilities into a class label that identifies the scenario with the highest probability.

3.8 Performance metrics

In the last few months, a collection of many studies have shown that there is a great deal of interest in the use of ROC curves to measure the performance of ML-based models. Some speculate it can be considered one of the main methods for measuring performance for ML methodologies [2, 4]. Here, we use the false-negative rate (FPR) and true-positive rate (TPR). We also make use of standard metrics such as accuracy, recall, precision, and F-measure. TPR is given as TPR = $\frac{TP}{TP+FN}$. Furthermore, FPR can be given as FPR = $\frac{FP}{FP+TN}$.

4 EXPERIMENTAL ANALYSIS AND DISCUSSION OF RESULTS

The emotional lexicon is built from the patient's own written texts, which serve as the basis for the emotional lexicon. Then the training is done on a separate architecture using the text representation. Transfer learning was performed using the Glove-based vectorizer. Moreover, both average vectorization and tagged vectors are used in the training for embedding. To further classify the data instances, a similarity-based method is used between the questionnaire and the text submitted by the patient. This is done by comparing the two. We used the Adam optimizer for each architecture, with the learning rate set to a maximum of 0.0005 per iteration [19]. We experimented with different cell types and varied the fraction of hidden space in each layout. In addition to the directed LSTM layer, an attention strategy was used to further improve the performance of the model. To store the model incrementally, the idea of early holding was used. We used a Central Processing Unit (CPU) and GPUs based on a 10^{th} generation Intel Core i7, and Nvidia Geforce RTX-2070, respectively.

In the past, we have changed the cell type and hidden size when working with deep neural architectures. To increase the performance of the model, we used the lexicon in conjunction with a fuzzy classifier in addition to the LSTM layer. In the empirical study, the models showed the problem of overfitting in both the development set and the testing set. To address these concerns, we run the model for a longer period. We also use early stopping to save time and fine-tune the processing of the model. In addition, we used the clipping approach to circumvent gradient problems [7]. As seen in Table 4, the attention method with fuzzy classification rules achieves a 0.89 F measure. We evaluated the architecture designed by considering the attention focus, aggregation of the focus and attention score, and using the activation output with and without a fuzzy classification model. Whenever a focus item exists in the attention-based model, it tends to perform better. However, in the absence of the focus word, attention networks miss classified the label. At the same time, the fuzzy model can successfully classify in both cases.

Table 4. The F-measure of the testing set.

Architectures	Test set
Baseline	0.85
Bidirectional LSTM	0.87
Bidirectional_LSTM_Attention	**0.88**
Bidirectional_LSTM_Attention with Fuzzy classification	**0.89**

Using different k fold values, we tested the embedding architecture, i.e., two, three, five, and ten folds. To check the detection performance under different epochs, we set the training/test set percentages as 0.50, 0.66, 0.80 and 0.90. The number of epochs is set to 50. Overall, all models can achieve a high F1 measure. However, the fuzzy classifier with rule-based configuration performed better despite the heavy unbalanced dataset, where symptom

Just Accepted

two is dominant in the dataset. The detection results of all LSTM architecture look similar to the small percentage of increase.

The model in Table 5 achieves a high recall of 0.87 but has the lowest accuracy of all models. The design is inefficient for the data at hand. The depression data depends on the order of the words, which the base network did not maintain. In other words, an architecture that prefers sequences and stores crucial word information is needed.

Table 5. K-fold approaches with variations on baseline model are used to calculate Precision, Recall and F-measure

	Precision	Recall	F-measure
2-Fold	0.78	0.81	0.79
3-Fold	0.84	0.81	0.82
5-Fold	0.84	0.85	0.84
10-Fold	0.84	0.87	**0.85**

4.1 Deep Attention model Analysis

In Tables 6 and 7, bidirectional LSTM is still able to achieve the similar performance of 0.87 as well as 0.88, respectively. The highest values are bold to represent the effective architecture concerning the number of folds. However, bidirectional LSTM with the attention model achieved 0.89 precision. The reason is that the model works in two directions: forward from the past to the future and backward from the future to the past. The two hidden state models maintain both future as well as past information. The two separate RNNs run in parallel, allowing backwards and forward connections between the networks. Both the training and evolution sets give the best results in terms of error reduction. The precision-recall are both quite good, as shown by the precision-recall curve in the upper right corner of the graph, which also indicates a low rate of false positives and negatives. The Bi-LSTM model takes into account any hidden state that depends on the state that preceded it. This poses a major challenge to the network, which must now wait for the data. Long-term dependencies can have a negative impact on performance because it is difficult to obtain information over a long period of time.

Table 6. K-fold approaches with variations on the Bidirectional LSTM model are used to calculate Precision, Recall and F-measure

	Precision	Recall	F-measure
2-Fold	0.78	0.77	0.77
3-Fold	0.83	0.81	0.82
5-Fold	0.83	0.87	0.85
10-Fold	0.88	0.87	**0.87**

4.2 Fuzzy rule classification analysis

The fuzzy classifier in Table 8 achieved high recognition and a very good accuracy score of 0.89. The fuzzy model also generated rules with extensible knowledge using the attention-based word list. With an increase in the cross-validation score, the fuzzy classifier performed better; this improved performance resulted in a high actual positive rate (TP). The results demonstrate the presence of essential terms that contribute significantly to and support the classification of depressive symptoms. In addition, the network contributes to cost reduction by focusing on specific phrases. This is because the model can recognize the target word of the task and learn the

Just Accepted

Table 7. *K*-fold approaches with variations on Bidirectional LSTM using a fuzzy classification attention model are used to calculate Precision, Recall and F-measure

	Precision	Recall	F-measure
2-Fold	0.81	0.81	0.81
3-Fold	0.86	0.84	0.85
5-Fold	0.89	0.87	**0.88**
10-Fold	0.81	0.87	0.84

Table 8. *K*-fold approaches with variations on Bidirectional LSTM fuzzy classification model are used to calculate Precision, Recall and F-measure

	Precision	Recall	F-measure
2-Fold	0.81	0.83	0.82
3-Fold	0.88	0.87	0.87
5-Fold	0.88	0.9	**0.89**
10-Fold	0.89	0.9	**0.89**

meaning of the topic in both directions. Thus, we can display the optimal model and evaluate its predictive power in randomized experiments.

Table 8 shows the performance of the network, which achieved a value of 0.89 in cross-validation. The model has a propensity to be too accurate. Since the sequential data in the primary network was not kept in its original order, the design did not perform very well. The sequential models can handle the sequential data and still give satisfactory results.

As mentioned in Table 4, the classification performance of our method with F1 score and lexicon expansion is at the highest possible value of 0.01, performing much better than other embedding methods that do not use lexicon expansion. Compared to embedding, the fuzzy lexicon set gives advantages greater than 0.05, between the values 0.82 and 0.77. This is the range where it is slightly superior. It is necessary to perform the tests indicated by the model over a longer period of time if the results are to be considered trustworthy. Since learning the representation from the contrast set requires language modeling, this factor contributes to an increase in instance weights. On the other hand, it has also been shown that as training time increases, the performance of the associated set of characteristics decreases. All classification approaches perform admirably when viewed as a collection of lexicon sentences. The bidirectional model, in conjunction with the attention network, can output critical work with emotional meanings and class links when paired with the attention network. The aggregation layers facilitate the generation of vector representations. In the method, suggestive words are analyzed to form phrases that are then linked together to identify symptoms in a conversation or written document. When certain words are deceptive and others are necessary, more weight is given to the crucial words compared to the surrounding phrases. The results show that expanding the vocabulary of the model and making minor grammatical adjustments can improve its overall performance. An approach to determining the relevance of sequences is presented in which attention-based weights are also added to a vector representation containing data. Then, this representation is combined with the representations of the different words to produce sentence vectors. This aggregated vector provides all the information about the pattern and semantic meaning needed to identify the instance class. The proposed system achieved a weighted F1 score of 0.82 thanks to the extension of the fuzzy set, which improved the accuracy of the training.

Machine learning has revolutionized data analytics for large-scale applications. Increasing privacy concerns in popular applications forced a reevaluation of traditional data training techniques. Semantic information

Just Accepted

gathered from the context in which semantic vectors reside is used to organize them. With the help of semantic information, the lexicon set facilitates the selection of an unlabeled text subset. The proposed method separates the unlabeled text and integrates it into the unsupervised learning process. The results show that there is a lexicon that contributes more to the classification of depressive symptoms. Moreover, the network helps to save computational resources by focusing on terms that contribute more to classification by using soft local attention. This is because the model has captured the meaning of the subject in both directions and can detect the target word in the challenge. Due to the complexity of mental health data, a more extensive vocabulary and grammatical variation can improve performance.

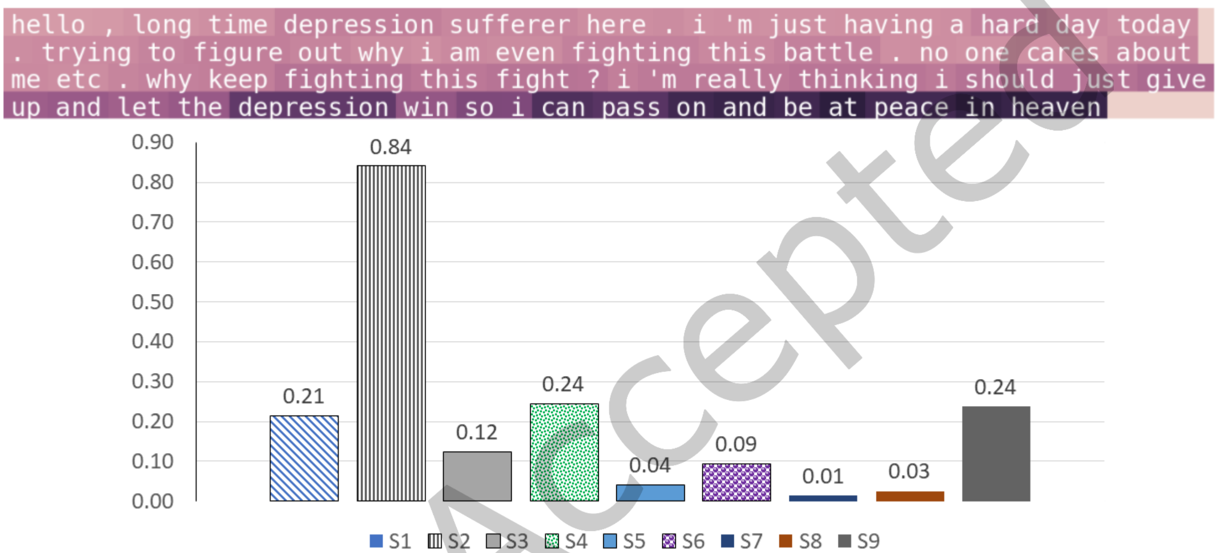

Fig. 3. An example patient authored text, symptom probability, fuzzy rule visualization of symptoms of depression extracted by our approach.

4.3 Visualization analysis and usage

Visualization illustrates the attention-based probability and triggered word rules of the sentence. The visualization allows the psychiatrist to see the reasons for the categorization in the diagnosis choice, such as the words *peace*, *heaven*, and *depression*. The highlighted weights yield 2 symptoms, namely $S3$ as well as $S2$ (hopelessness/feeling down). The fuzzy approach can successfully identify and highlight focused words that can help psychiatrists in patient assessment and diagnosis. The fuzzy model can successfully identify triggering rules and highlight focused words that can help psychiatrists make definitive diagnoses. Visualization helps to understand the context behind the extraction of symptoms. The attention model supported by fuzzy rules makes the system more explainable and less complex. As shown in Fig. 3, dark highlighted words trigger the decision. The proposed model helps to understand the reasons behind the prediction. The intention of the prediction model helps to support decision-making. When a psychiatrist sees an irregularity, he/she can detect it using word attention and fuzzy rules.

Just Accepted

4.4 Discussion

Prediction of future values is entirely satisfactory, even when data is highly non-linear. The accuracy of prediction can be arbitrarily fixed to an acceptable limit by increasing membership functions over the data domain. With every prediction, a new rule is added to the rule base. Thus, the 'quality of prediction keeps on increasing. Because of their similarity to human control logic, fuzzy controllers have proven to be an excellent choice for various control systems. They can be incorporated into anything from a small handmade item to a primarily automated processing control system. Due to their superior performance, high reliability, and durability, fuzzy-based controllers have become very competitive in today's market. The current research does not need a sophisticated thought process. It was simply beautiful as well as easy to apply. The proposed application demonstrates a straightforward method to arrive at a final result based on confusing, inaccurate, noisy or missing input data. The fuzzy logic controller method for problem-solving simulates how a human might make a decision more quickly. Because the system does not require perfect, noise-free inputs, it is resilient. Despite a wide range of input variations, the output control is a smooth control function. The controller consists of user-defined rules that control the target system, as well as it can be easily updated to improve the system's performance significantly. New symptoms can be easily incorporated into the system by developing appropriate control rules. The fuzzy controller is not bound to a small number of inputs or outputs. It allows low-cost and imprecise extraction of symptoms, making the whole system cost-effective and straightforward.

5 CONCLUSION AND FUTURE DIRECTIONS

The expansion of emotional lexicons is the focus of this research, which explores the notion of embedding. The fuzzy model then uses embedding to arrive at insights and categorize symptoms. Bidirectional LSTM gates are used to generate the emotionally relevant embedding for the fuzzy inference system using the proposed method. According to our research results, fuzzy logic components can not only deal with ambiguity but also accurately comprehend the operation of the embedding. The fuzzy-based model successfully achieved an F value of 0.89 for the similarity-based labeled data. Moreover, the model can extend its knowledge by making the selection dependent on entropy. The classification-based association rules are used as a starting point for developing fuzzy logic rules. As proposed, the strategy resulted in an adaptation of the IDPT system that allowed him to independently expand his understanding of the symptoms. The modified intervention provides personalized feedback on the activities recommended. To improve the detection rate, we plan to use automatic rule generation techniques and dynamic architecture search in the future. Based on our findings, the fuzzy recurrent attention model was as effective in its interpretive analysis as it was in its performance. To facilitate the performance of the prediction tasks, the improved version had to include the visual features of the patients.

REFERENCES

[1] Juan Aguilera, Delia Irazú Hernández Farías, Rosa María Ortega-Mendoza, and Manuel Montes-y Gómez. 2021. Depression and anorexia detection in social media as a one-class classification problem. *Applied Intelligence* (2021), 1–16.

[2] Usman Ahmed, Muhammad Aleem, Yasir Noman Khalid, Muhammad Arshad Islam, and Muhammad Azhar Iqbal. 2019. RALB-HC: A resource-aware load balancer for heterogeneous cluster. *Concurrency and Computation: Practice and Experience* (2019), e5606.

[3] Usman Ahmed, Jerry Chun-Wei Lin*, and Gautam Srivastava. 2022. Fuzzy Contrast Set Based Deep Attention Network for Lexical Analysis and Mental Health Treatment. *Transactions on Asian and Low-Resource Language Information Processing* (2022).

[4] Usman Ahmed, Jerry Chun Wei Lin, Gautam Srivastava, and Muhammad Aleem. 2020. A load balance multi-scheduling model for OpenCL kernel tasks in an integrated cluster. *Soft Computing* (2020), 1–14.

[5] KS Arikumar, Sahaya Beni Prathiba, Mamoun Alazab, Thippa Reddy Gadekallu, Sharnil Pandya, Javed Masood Khan, and Rajalakshmi Shenbaga Moorthy. 2022. FL-PMI: federated learning-based person movement identification through wearable devices in smart healthcare systems. *Sensors* 22, 4 (2022), 1377.

[6] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In *The International Conference on Learning Representations*, Yoshua Bengio and Yann LeCun (Eds.). ICLR, 24–34.

Just Accepted

[7] Xiangyi Chen, Steven Z Wu, and Mingyi Hong. 2020. Understanding gradient clipping in private SGD: A geometric perspective. *Advances in Neural Information Processing Systems* 33 (2020), 1–10.

[8] Edward Choi, Mohammad Taha Bahadori, Andy Schuetz, Walter F Stewart, and Jimeng Sun. 2016. Doctor ai: Predicting clinical events via recurrent neural networks. In *Machine learning for healthcare conference*. 301–318.

[9] Palash Dutta and Soumendra Goala. 2018. Fuzzy decision making in medical diagnosis using an advanced distance measure on intuitionistic fuzzy sets. *The Open Cybernetics & Systemics Journal* 12, 1 (2018).

[10] Robin C Feldman, Ehrik Aldana, and Kara Stein. 2019. Artificial intelligence in the health care space: how we can trust what we cannot know. *Stan. L. & Pol'y Rev.* 30 (2019), 399.

[11] Jiří Filip and Tomáš Kliegr. 2018. *Classification based on Associations (CBA)-a performance analysis*. Technical Report. EasyChair.

[12] Xiaoqing Gu, Kaijian Xia, Yizhang Jiang, and Alireza Jolfaei. 2021. Multi-task Fuzzy Clustering–Based Multi-task TSK Fuzzy System for Text Sentiment Classification. *Transactions on Asian and Low-Resource Language Information Processing* 21, 2 (2021), 1–24.

[13] David Gunning. 2017. Explainable artificial intelligence (xai). *Defense Advanced Research Projects Agency (DARPA), nd Web* 2, 2 (2017).

[14] Alex Holub, Pietro Perona, and Michael C Burl. 2008. Entropy-based active learning for object recognition. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 1–8.

[15] Andreas Holzinger, Georg Langs, Helmut Denk, Kurt Zatloukal, and Heimo Müller. 2019. Causability and explainability of artificial intelligence in medicine. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 9, 4 (2019), e1312.

[16] Nasir Jamal, Chen Xianqiao, Fadi Al-Turjman, and Farhan Ullah. 2021. A Deep Learning–based Approach for Emotions Classification in Big Corpus of Imbalanced Tweets. *Transactions on Asian and Low-Resource Language Information Processing* 20, 3 (2021), 1–16.

[17] Kipp W Johnson, Jessica Torres Soto, Benjamin S Glicksberg, Khader Shameer, Riccardo Miotto, Mohsin Ali, Euan Ashley, and Joel T Dudley. 2018. Artificial intelligence in cardiology. *Journal of the American College of Cardiology* 71, 23 (2018), 2668–2679.

[18] Christian Karmen, Robert C. Hsiung, and Thomas Wetter. 2015. Screening Internet forum participants for depression symptoms by assembling and enhancing multiple NLP methods. *Computer Methods and Programs in Biomedicine* 120, 1 (2015), 27–36.

[19] Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014).

[20] Chayakrit Krittanawong, HongJu Zhang, Zhen Wang, Mehmet Aydar, and Takeshi Kitai. 2017. Artificial intelligence in precision cardiovascular medicine. *Journal of the American College of Cardiology* 69, 21 (2017), 2657–2664.

[21] Kurt Kroenke, Robert L. Spitzer, and Janet B.W. Williams. 2001. The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine* 16, 9 (2001), 606–613.

[22] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. 2015. Deep learning. *nature* 521, 7553 (2015), 436–444.

[23] Daniel M Low, Laurie Rumker, Tanya Talkar, John Torous, Guillermo Cecchi, and Satrajit S Ghosh. 2020. Natural Language Processing Reveals Vulnerable Mental Health Support Groups and Heightened Health Anxiety on Reddit During COVID-19: Observational Study. *Journal of medical Internet research* 22, 10 (2020), e22635.

[24] Thang Luong, Hieu Pham, and Christopher D. Manning. 2015. Effective approaches to attention-based neural machine translation. In *The Conference on Empirical Methods in Natural Language Processing*, Lluís Màrquez, Chris Callison-Burch, Jian Su, Daniele Pighin, and Yuval Marton (Eds.). 1412–1421.

[25] George Miller, Christiane Fellbaum, Judy Kegl, and Katherine Miller. 2009. WordNet: An Electronic Lexical Reference System Based on Theories of Lexical Memory. *Revue québécoise de linguistique* 17, 2 (2009), 181–212.

[26] Julia Mühleck, Sigrid Borse, Eva Wunderer, Bernhard Strauß, and Uwe Berger. 2019. Online-Befragung zur Bekanntheit von Angeboten zur Aufklärung, Prävention, Beratung und Nachsorge bei Essstörungen. *Prävention und Gesundheitsförderung* 15, 1 (2019), 73–79.

[27] Suresh Kumar Mukhiya, Usman Ahmed, Fazle Rabbi, Ka I Pun, and Yngve Lamo. 2020. Adaptation of IDPT System Based on Patient-Authored Text Data using NLP. In *IEEE International Symposium on Computer-Based Medical Systems*. IEEE, 27–36.

[28] Antoine Neuraz, Ivan Lerner, William Digan, Nicolas Paris, Rosy Tsopra, Alice Rogier, David Baudoin, Kevin Bretonnel Cohen, Anita Burgun, Nicolas Garcelon, et al. 2020. Natural language processing for rapid response to emergent diseases: Case study of calcium channel blockers and hypertension in the COVID-19 pandemic. *Journal of medical Internet research* 22, 8 (2020), e20773.

[29] World Health Organization et al. 1993. *The ICD-10 classification of mental and behavioural disorders: diagnostic criteria for research*. Vol. 2. World Health Organization.

[30] Sharnil Pandya, Thippa Reddy Gadekallu, Praveen Kumar Reddy, Weizheng Wang, and Mamoun Alazab. 2022. InfusedHeart: A novel knowledge-infused learning framework for diagnosis of cardiovascular events. *IEEE Transactions on Computational Social Systems* (2022).

[31] Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In *The Conference on Empirical Methods in Natural Language Processing*. 1532–1543.

[32] Bornali Phukon, Akash Anil, Sanasam Ranbir Singh, and Priyankoo Sarmah. 2021. Synonymy Expansion Using Link Prediction Methods: A Case Study of Assamese WordNet. *Transactions on Asian and Low-Resource Language Information Processing* 21, 1 (2021), 1–21.

[33] Alvin Rajkomar, Eyal Oren, Kai Chen, Andrew M Dai, Nissan Hajaj, Michaela Hardt, Peter J Liu, Xiaobing Liu, Jake Marcus, Mimi Sun, et al. 2018. Scalable and accurate deep learning with electronic health records. *NPJ Digital Medicine* 1, 1 (2018), 1–10.

Just Accepted

[34] Sujata Rani and Parteek Kumar. 2021. Aspect-based Sentiment Analysis using Dependency Parsing. *Transactions on Asian and Low-Resource Language Information Processing* 21, 3 (2021), 1–19.

[35] Alejandro Santiago, Bernabé Dorronsoro, Antonio J Nebro, Juan J Durillo, Oscar Castillo, and Héctor J Fraire. 2019. A novel multi-objective evolutionary algorithm with fuzzy logic based adaptive selection of operators: FAME. *Information Sciences* 471 (2019), 233–251.

[36] Chengai Sun, Liangyu Lv, Gang Tian, and Tailu Liu. 2020. Deep interactive memory network for aspect-level sentiment analysis. *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)* 20, 1 (2020), 1–12.

[37] Emily A. Troyer, Jordan N. Kohn, and Suzi Hong. 2020. Are we facing a crashing wave of neuropsychiatric sequelae of COVID-19? Neuropsychiatric symptoms and potential immunologic mechanisms. *Brain, Behavior, and Immunity* 87 (2020), 34–39.

[38] Alfredo Vellido. 2019. The importance of interpretability and visualization in machine learning for applications in medicine and health care. *Neural computing and applications* (2019), 1–15.

[39] Fei Wang, Rainu Kaushal, and Dhruv Khullar. 2020. Should health care demand interpretable artificial intelligence or accept "black box" medicine?

[40] Kun Wang, Yanpeng Cui, Jianwei Hu, Yu Zhang, Wei Zhao, and Luming Feng. 2020. Cyberbullying detection, based on the fasttext and word similarity schemes. *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)* 20, 1 (2020), 1–15.

[41] Yan Xiang, Zhengtao Yu, Junjun Guo, Yuxin Huang, and Yantuan Xian. 2021. Event Graph Neural Network for Opinion Target Classification of Microblog Comments. *Transactions on Asian and Low-Resource Language Information Processing* 21, 1 (2021), 1–13.

[42] Lingling Xu, Ruyi Jin, Feifei Huang, Yanhui Zhou, Zonglong Li, and Minqiang Zhang. 2020. Development of Computerized Adaptive Testing for Emotion Regulation. *Frontiers in Psychology* 11 (2020), 3340.

[43] Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. 2016. Hierarchical attention networks for document classification. In *The Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 1480–1489.

Just Accepted