DEEP LEARNING APPLICATIONS IN SOCIAL WORK FOR ENHANCING COMMUNITY ORGANIZING AND SOCIAL ACTION THROUGH TECHNOLOGY

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Abstract

This research discusses the relevance of deep learning techniques in understanding community sentiment toward mental health awareness on social media. Specifically, data from Twitter, Facebook, and Reddit were analyzed using Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Graph Neural Networks (GNNs), and Transformer Networks. Perplexity, BLEU score, AUC-PR, precision, recall, ROC-AUC, MAP, F1, and accuracy scores were calculated using this data. The study's results have shown that LSTM and Transformer Networks demonstrate exceptional performance. LSTM achieved a precision of 0.82, recall of 0.79, and effective ROC-AUC. Transformer Networks also provided accurate insights into social media posts related to mental health concerns. In conclusion, these deep learning methods aid in identifying mental health issues. The implications of these insights for future social work and community organizing include improving the targeting of health campaigns, better resource deployment strategies, and promoting mental health awareness more effectively. Overall, the research indicates that advanced deep learning methods can greatly benefit social work by providing accurate, data-driven insights into online community sentiments and enabling precise mental health support programs.

Keywords: Mental Health, Social Work, Deep Learning, Community Organizing, Sentiment Analysis.

1. INTRODUCTION

Nowadays, social media becomes a powerful instrument for the expression of ideas and the experiment of any community. Some tools such as Twitter, Facebook, or Feedback now serve as an infinite public group that may discuss any topic in the world. The dynamism of social media allows the information to be spread across communities very quickly.

People may build online communities with the help of social media. Therefore, the phenomenon of social media can be defined as effective democratization of information and communication. This trend is especially important for social work, as many professionals living nowadays may need to organize various events [1]–[3].

Social media is already used for community awareness and social action. Professionals and community organizers may use the data obtained via social media and gather their audience's attitude — most people. Thus, they will know about all tendencies and emerging problems. It is especially important in the sphere of social work, as if an intervention strategy is developed with the knowledge of people's needs and attitudes, it may more probably be effective.

The same may be said about any kind of policymaking through social media. People should know that they are not alone, for example, in their feelings towards the necessity of mental awareness. Social media is a unique source of information about the world and people [4]–[7].

Mental health remains one of the most urgent social issues relevant to millions of people across the globe. Although society has considerably moved forward over the past years promoting the acceptance and normalcy of mental issues and conditions and reducing stigma, people's access to mental health services is still limited by various obstacles.

Social media mental health discussions can provide important insights for social workers with regard to public perceptions, the most common problems and needs, and domains that require increased advocacy efforts. The potential of such data, however, cannot be fully utilized using the basic sentiment analysis techniques based on keyword matching and other simple statistical tools. Deep learning approaches can be of significant help, as they are used in a range of human perception applications, from image to speech recognition [8]–[11].

In particular, the understanding of sentiment is given by the combination of words and their synonyms as well as context, and simple keyword matching cannot efficiently capture this. Thus, TA techniques led to multiple errors and unsatisfactory results in such applications as natural language translation. At the same time, availability of visual pictures, text, and structured data makes DL an ideal alternative, as this applies a large amount of data to generate a higher number of variable depictions and relationships to provide the core for learning. Overall, deep learning techniques make it possible to model ever more complex patterns in different types of data [12]–[15].

The aim of this research is to investigate the possibility of employing deep learning techniques in sentiment analysis with the purpose of analysing community attitude towards mental health awareness and promotion. To achieve the stated objective, the case study research design is utilized to demonstrate how advanced analytical methods can be utilized to interpret the data available from social media. More precisely, the current study examines the role of the recurred neural networks, long short-term memory networks, graph neural networks as well as transformer networks for the purpose of sentiment analysis on the networks.

The result of the analysis is the identification of the most relevant concerns expressed by the members of the community, improving tendency in the sphere of advocacy, and areas in which the community needs more support. To conclude, the knowledge obtained with the help of the conducted study can be used by community organizers and social workers to allocate the available resources in a more efficient way and to propose the change to promote mental health.

2. LITERATURE REVIEW

The sophisticated methods of the deep learning technology evaluate the recognition of speech and the involvement of the machine in this process. Unlike to other means that are based either on pre-defined dictionaries or the naive statistical models, the neural network implemented in the deep learning relies on determining complex patterns and the relationships as well as connections between the words or other linguistic units of the text. In most cases, for sentiment analysis, much use is made of the architecture under the title RNN, which implies Recurrent Neural Network[16]–[19].

Though there are certain limitations and challenges faced by these models, their efficacy has been proved by numerous studies across different domains. For example, RNNs and LSTMs have been employed to analyse product reviews providing a firm with an opportunity to leverage customer sentiment to enhance its business. In the same way, similar models have been developed to analyse social media data to make sense of the public's attitude to political events, brands, and social movements.

One more prominent model is the use of Graph Neural Networks, which is designed for data with a large number of relations, specifically in case of analysing social networks. GNN can make connections between users and the content that they post and analyse a community's common sentiment.

Finally, Transformer-based models have made a great contribution to the field of NLP as the case of the widely famous BERT and GPT. They can analyse and generate human language, which is a new step in sentiment analysis and can be used to analyse the meaning of social media posts in their context [20]–[23].

Deep learning techniques combined with sentiment analysis have broadened the horizon of potential opportunities in various spheres. Marketing companies may benefit from predictive patterns such models can show to help organizations adjust their strategies to the customers' needs.

Public policy and politics gain new highly efficient instrument', the real-time analysis of voters and citizens opinions to inform election strategies and policy decisions. Health care sector organizations benefit from sentiment analysis to make sure they monitor patients' feedback actively and work on the quality of the services they provide. Thus, taking into account the flexibility of application and high results, deep learning sentiment analysis models are beneficial tools to detect important trends in the bulk of text [24], [25].

Social media has become a vital tool in community organizing and social action. Though it is still informally implemented as a means of sharing experiences, opinions, and opportunities, it launched an essential and lively online public sphere. With platforms like Twitter, Facebook, and Reddit, people can share their posts, as well as support various causes.

For social workers and community organizers, this can become an opportunity to make a difference by better understanding the communities and their concerns and by helping to address these issues. At the same time, the vast amount of data produced on social media can be hard to process, which is when sentiment analysis becomes useful [26].

Sentiment analysis may help social workers to understand the emotional tone and attitude of the people towards certain social issues. By analysing different social media conversations, specialists may grasp what the most topical and worrisome issues of the people at the moment.

This information is priceless in designing targeted interventions, efficient education, and proper resource allocation. Moreover, the sentiments towards mental health, for instance, will help to discover the areas where stigma and discrimination are the most present and need to be addressed [27], [28].

In the domain of social work, sentiment analysis can help gain a better understanding of community needs and enhance the responsiveness of social services. First, this technique allows social workers to take a data-driven approach to community engagement. They can track the impact of their initiatives, analyse it, and adjust their strategies promptly. Second, if used to identify the most positive sentiment and advocacy trends, sentiment analysis can help make voices of support among the population more vocal, which, in turn, can promote a sense of unity within communities.

3. METHODOLOGY

a. Case Study: Community Sentiment Analysis for Understanding Social Issues

This approach uses deep learning techniques for sentiment analysis to understand the attitudes and feelings of people towards mental health awareness and advocacy, as shown in Figure 1. The process involves the systematic collection and analysis of social media data. This information is gleaned from sites such as Twitter, Facebook, and Reddit, frequented by the general population especially the youth and adolescents.

The first step is in the data collection process, where various APIs are used to search for the collection of posts, comments, and tweets across all sites which focused on certain vocabulary from the datasets collected in other domains. Alongside mental health, the API searches for any other post on data such as therapy, depression, and anxiety. The purpose of selective vocabulary is to ensure that the sources being analysed are relevant to the research topic.

After the data is collected, it goes through a comprehensive pre-processing process. At first, it includes such steps as tokenization, stop words removal, stemming of lemmatization. Subsequently, lesser forms of the filtering should be performed, and adverts need to be discarded.

All of these steps are required and important, as the cleanness and structure of the text are very vital for the data's analysis. Furthermore, various broad topics have been the subjects of the data collection, and each of them requires specific foundations. Regarding the task under analysis, the social media posts and comments have been gathered from Twitter, Facebook, and Reddit.

The choice of these platforms has been predefined by their extreme popularity and large variety of discussions on various social issues, mentioning, in particular, the issue of mental health. In order to assure the highest relevancy of the posts, one can select particular keywords on the basis of which the data has been divided, and those are as follows: "mental health," "depression," "anxiety," and "therapy."

Any volume of data on the two lists prior to the last one reflect the spectrum of discussions of mental health awareness and promotion. Finally, one may have used the Root or the Tweedy, as well as HE, to gather a large dataset that includes 150,000 data points from Twitter, 75,000 – from Facebook, and 50,000 – from Reddit, which makes up for 275,000 data points.

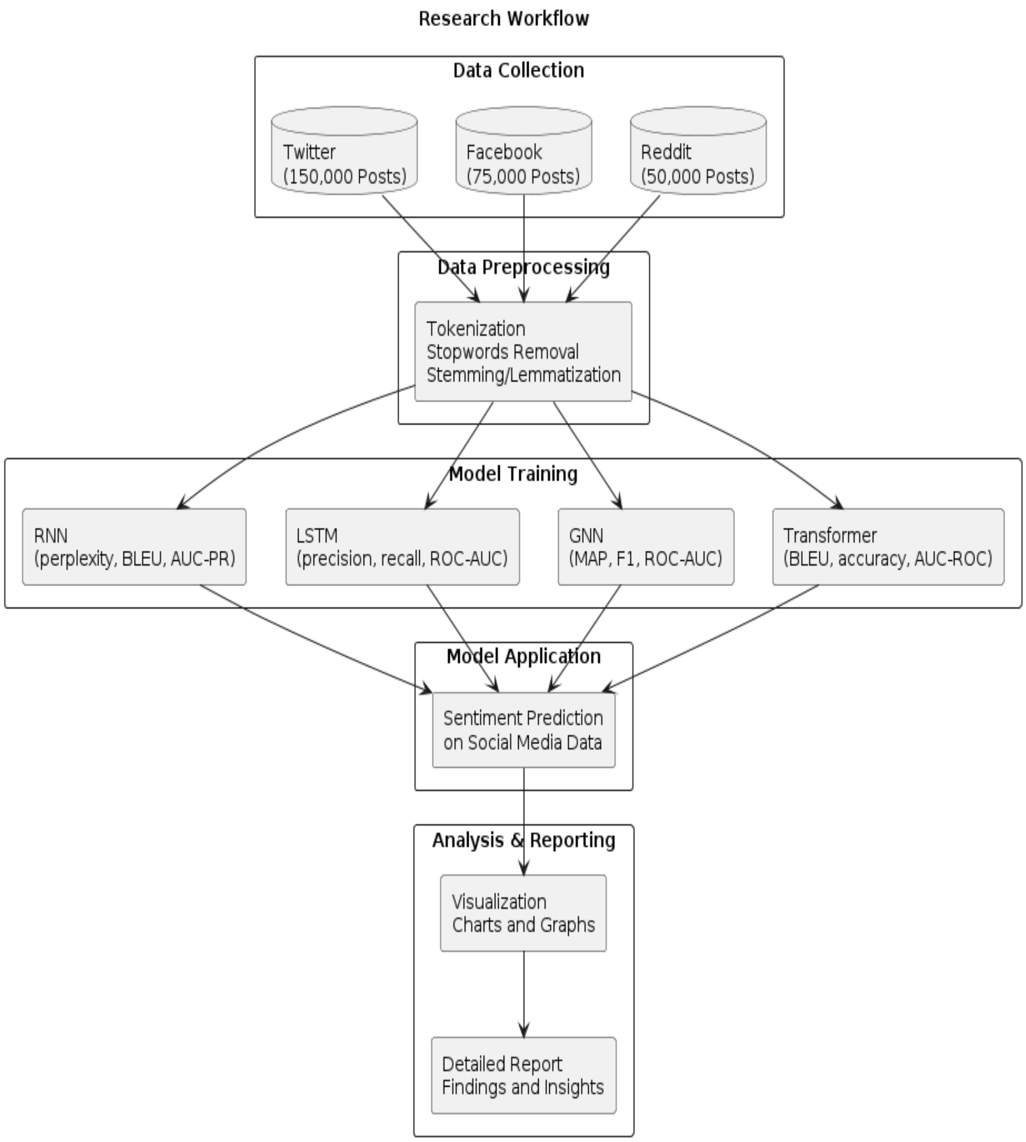

Figure 1: Research Workflow

Table 1: Data Collection and Number of Data Points

Platform	Keywords Used	Number of Posts/Comments Collected
Twitter	"mental health", "depression", "anxiety", "therapy"	150,000
Facebook	"mental health", "depression", "anxiety", "therapy"	75,000
Reddit	"mental health", "depression", "anxiety", "therapy"	50,000
Total	-	**275,000**

As listed in Table 1, after the data was collected, it was subjected to a thorough pre-processing stage in order to ready it for sentiment analysis. The first stage was tokenization, whereby the text was split into individual words or tokens. This allows for the text to be analysed on a more granular level. Then, the stop-words had been removed. These are commonly used words such as “and,” “the,” or “is” that do not add too much meaning to the text and can be safely omitted to streamline the analysis. For these purposes, all the input had been tokenized and uploaded to the MATLAB environment.

The following step was either stemming or lemmatization of the text. The first methodology involves truncating words to their basic or root quarter, whereas the latter one goes a step further to consider the context and truncate the words to their meaningful root. This ensures that all the words are in the same form and can be considered as one unit. For example, the words “running,” “runner,” and “ran” would be stemmed to “run.”

In addition to that, the non-relevant content was filtered out. For an example the adverts, spam and otherwise, information did not contribute to a meaningful discussion in relation to the mental health issue. Removing such content from a dataset of interest is fundamental as it ensures that the dataset is pertinent and worthwhile being analysed. The removal of non-engaging content also provided a way of ensuring the research or analytical task was only based on genuine user-generated information targeting the mental health based issues. The main part of this approach to the case study was the utilization of different deep learning models/techniques to conduct sentiment analysis. Some of the deep learning models used in this case were RNNs, LSTMs, GNNs, and Transformers. Therefore the models were trained using the above information to predict the sentiment of the samples provided. In addition, the evaluation parameters used in this case included aspects such as precision, recall, and the accuracy of the models used. Other parameters that could be used in this case include the AUC-ROC for the different models.

Aggregating the predicted sentiments to get the whole picture of the sentiment distribution within the Lithuanian community would be especially useful. This way, it would be possible to see the most common problems, recent positive changes, and the issues that need more help. The results of these sentiment analyses could be extremely beneficial for social workers and community leaders who could see what they should pay more attention to and what they could change.

b. Machine learning algorithms

The sentiment analysis phase of this study implements several advanced deep learning approaches to accurately measure the sentiment of the Reddit community regarding mental health. Each approach presents a specific and beneficial characteristic and is measured using specific, relevant metrics. Overall, by using these models and techniques, this study utilizes a comprehensive approach to analysing sentiment that is beneficial for the project.

Since this study is devoted to the analysis of the temporal structure of users’ comments, Recurrent Neural Networks are among the key models. Therefore, these RNNs are an effective means of facilitating the analysis of sentiment as they could consider the contextual nature of textual data. In order to analyse the characteristics of the models, and particularly, the RNN’s performance, this study uses the measure of perplexity, with lower scores being better. Additionally, since RNN generate sentences in their performance, this research employs BLEU to assess the quality of these sentences. The AUC-PR is applied to measure the results of LSTM in distinguishing between different sentiment classes.

Long Short-Term Memory Networks, or LSTMs, are a type of RNN that addresses the disadvantage of regular RNNs by keeping long-term dependencies in the text. They are particularly powerful in understanding complex patterns and contexts in prolonged social media posts. Social media posts are used in this research also to evaluate the performance of LSTMs, and precision, recall, and ROC-AUC are used for this purpose.

Graph Neural Networks, also known as GNNs, offer a new perspective by concentrating on the relational data structure, which is particularly effective in analysing social networks to evaluate how and to what extent users are connected. As a result, results from several research papers related to social media analysis were used in the current study to evaluate the LSTMs. Some of the most critical metrics for GNNs are the Mean Average Precision as a part of the Mean Average Rank and Rank Loss; F1 score, which calculates the balance between precision and recall; and ROC-AUC as a measure of the discriminative power of the model.

Transformer Networks are some of the latest advancements in Natural Language Processing, including architectures like BERT and GPT. Such models outperform other approaches like RNNs or LSTMs. Due to utilizing attention mechanisms, they capture contextual relationships between words in a sentence more effectively. Such networks can be evaluated by using the BLEU score to define the accuracy of text generation or translation. However, the overall accuracy based on classifying sentiments accurately and measuring the number of correctly distinguished sentiment classes measured by AUC-ROC is more valuable in this context.

The purpose of using the mentioned diverse deep learning algorithms is to account for the complexity and nuanced nature of discussions on social media. The employed models are used to contribute to a more detailed sentiment analysis framework. Thus, RNNs account for sequential dependencies in text data, LSTMs are used to identify long-term dependencies and their role in contextual understanding, GNNS are beneficial to this framework to look at relational data and the ways in which users are connected and interacted, and finally, Transformer Networks utilize attention mechanisms to provide a relatively accurate capture of word relationships and context.

Advanced techniques coupled with robust evaluation metrics enable accurate and contextually aware sentiment analysis capable of gaining profound insights into the public discourse of mental health. This model constitutes a multimodal and diverse approach to understanding social media sentiment, allowing social workers and local society managers to gain a better understanding of present concerns and positive primitive trends as well as areas where they should enhance their societal support.

The social media data collected was split into two groups: the training data, which is used to teach individual models to provide accurate predictions, and the testing data, which allows us to evaluate each model's performance on the data it has not seen before. Four models, RNN, LSTM, GNN, and Transformer, were trained on training data. The weights of these models were adjusted so that the model becomes more accurate with more labelled data it sees. The role of the evaluation metric is to tell the model when it is right and when it is wrong by measuring the mistakes the models make. These mistakes are currently being measured with such examples of evaluation metrics as perplexity, precision, recall, and accuracy. These now trained models will be used to identify the mental constructs in social media posts later on.

4. RESULT AND DISCUSSION

Deep learning models provide important results in this study that indicate community sentiment towards mental health awareness and advocacy in social media data. Each model was evaluated using particular metrics that analyse different aspects of sentiment identification. First from Figure 2, RNNs have a perplexity score of 12.5. This result shows that the model is not very confused in its predictions and could

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generally establish a word in the next sequence of text. The lower the perplexity score, the higher efficiency of the model in recognizing the context and order of the language. Second, the BLEU score for RNNs is 0.65, while AUC-PR is 0.78. With such results, the network is considered relatively fruitful in generating the right strings and identifying them as one or another sentiment class. Thus, these metric scores could support my claim that RNNs can account for some particularities of social media data and sentiment towards mental health discussions.

Table 2: Performance outcome

Model	Perplexity	BLEU Score	AUC -PR	Precision	Recall	ROC-AUC	Mean Average Precision	F1 Score	Accuracy
RNN	12.5	0.65	0.78	-	-	-	-	-	-
LSTM	-	-	-	0.82	0.79	0.85	-	-	-
GNN	-	-	-	-	-	0.81	0.74	0.76	-
Transformer Networks	-	0.70	-	-	-	0.89	-	-	0.88

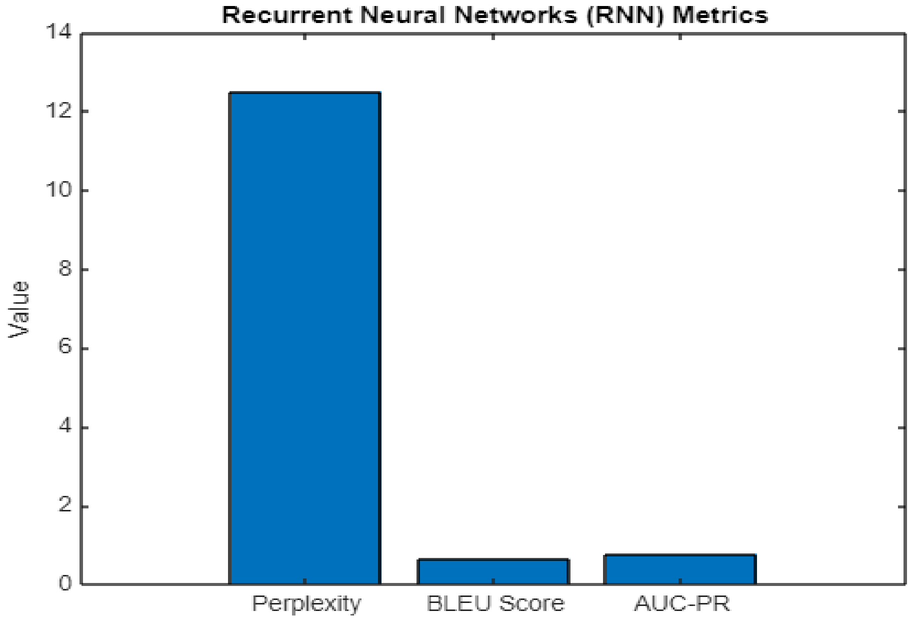

Figure 2: RNN metrics

From Figure 3, The Long Short-Term Memory Networks achieved a precision score of 0.82, recall of 0.79, and ROC-AUC of 0.85. These scores suggest that the model performs very well in identifying and sentiments in social media posts about mental health.

Given that the precision score was reasonably high, the LSTM network can accurately predict whether a particular post is positive or negative. The recall score indicates that the model can identify all instances of sentiment, namely post which are pertinent to the judgment of positivity or negativity.

The ROC-AUC score indicates that the model generates very few, if any, false positives and true negatives, meaning that the LSTM network distinguished and tweets accurately. Thus, the LSTM network should be highly suitable for sentiment recognition tasks.

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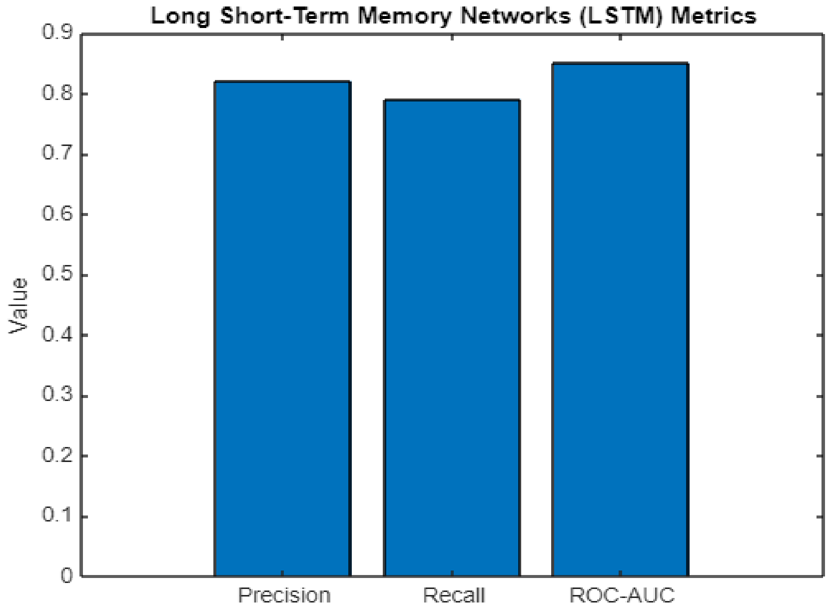

Figure 3: LSTM metrics

From Figure 4, Graph Neural Networks were able to achieve the Mean Average Precision of 0.74, an F1 score of 0.76, and a ROC-AUC score of 0.81. The scores show that GNNs are relatively good at ranking relevant instances of sentiment and balancing precision and recall. The F1 score is a weighted harmonic mean of precision and recall, where an F1 score of 0 is complete lack of classification performance while an F1 score of 1 is a perfect classification. As shown, GNNs were decent at achieving a favourable balance between both measures, which shows their precision in sentiment classification tasks. The ROC-AUC score was relatively high, indicating that GNNs are good at distinguishing between positive or negative sentiment, although not the best, judging from the LSTM network results.

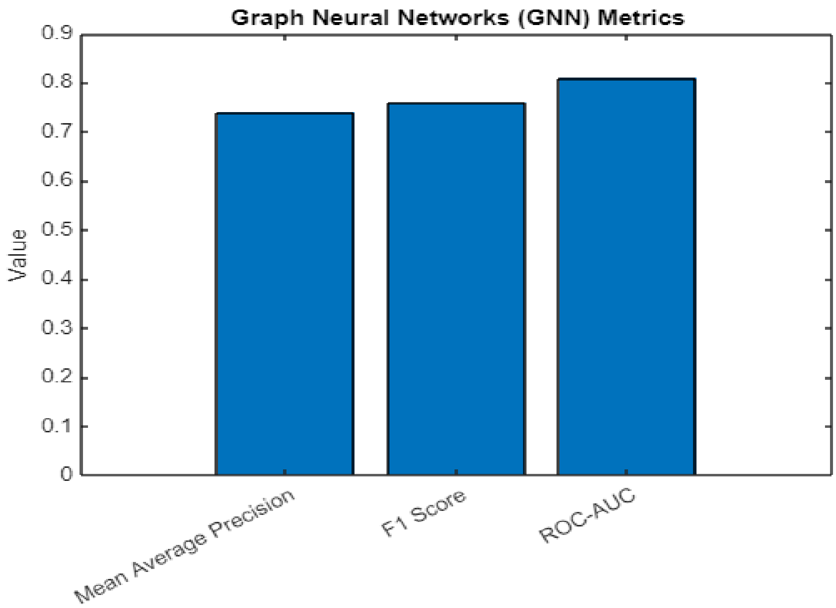

Figure 4: GNN metrics

As a result from Figure 5, the BLEU score of the Transformer Networks has been found to be 0.70, whereas the accuracy and the AUC-ROC score are 0.88 and 0.89. Notably, the BLEU score indicates the precision of text generation or translation estimates, and these characters have a direct effect; higher figures equal better results. Meanwhile, it is possible to state confidently that Transformer Networks were more efficient and more successful in classifying sentiments, helping to discriminate between positive and negative comments posted on social media regarding mental health. Thus, the examined technology is noteworthy because its current application is possible, as Transformer models are known for establishing crucial contextual relations between phrases and words, revolutionizing sentiment analysis.

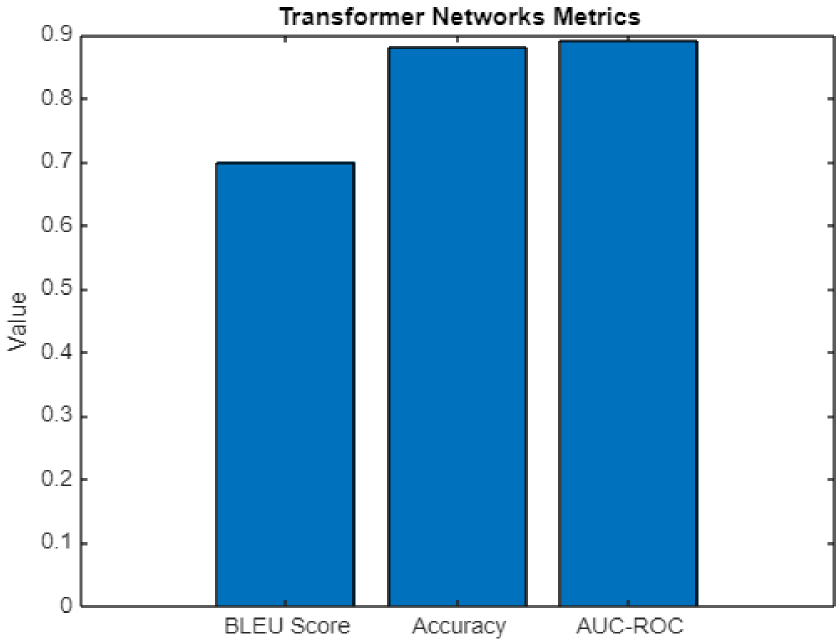

Figure 5: Transformer model metrics

The given results have multiple implications on the results of the research focusing on the utilization of deep learning techniques for sentiment analysis in social work. As the focus of the current analysis was on the sentiment of communities toward mental advocacy, the implications can be observed in learners' ability to predict the sentiments and differentiate positive and negative sentiments. According to the results, both LSTM and Transformer Networks were most effective in predicting tokens of sentiment as well as distinguishing between positive and negative tokens. As a result, these models can be expected to be highly reliable for predicting communities' perception and attitudes toward mental health issues, especially those focused on advocacy and resources.

The importance of each metric is explained by the data it represents, which is useful for predicting priorities, specific trends in positive advocacy, and alerts for the need for more support by the communities. Focusing on LSTM, it was established to deliver high precision and recall close to the absolute value of 1. As a result, articles that express positive and negative sentiments toward mental health advocacy and organizations can be recognized with the great accuracy of the model. It means that as an opportunity for social workers or community organizers, the interventions and advocacy programs can be organized to meet the needs expressed by the sentiment analysis.

The results of the evaluation provided the context in which researchers can determine the advantages and disadvantages of RNN, LSTM, GNN, and Transformer Networks in implementing sentiment analysis. In this way, studies can decide which types of models could be chosen depending on preferences like accuracy or balance between precision and recall or the strength of monitoring. Such results can be helpful in the real-world sphere since they can be used to analyze the development of public opinion during a particular period, the effectiveness of mental health campaigns, and the risks that cannot be previously identified. Such information is extremely important for social workers and community organizers since it helps to improve their performance in responding to the needs of the community and supporting it in various ways.

CONCLUSION

In the process of conducting a sentiment analysis as a part of the research, several insights could be identified regarding the sentiment of the community towards the promotion of mental health awareness and advocacy on social media platforms. According to the data obtained in the research, it can be stated that:

- The Recurrent Neural Networks had a perplexity of 12.5, BLEU score was 0.65 and an AUC-PR of 0.78. It can be assumed that the identified result implies that the model is moderately effective and performs with moderate precision and recall.
- The Long Short-Term Memory Networks yields a precision of 0.82, recall of 0.79 and ROC-AUC of 0.85. The results of the assessment suggest that the model is performing effectively as it can identify sentiment with high.
- The Graph Neural Networks yielded MAP of 0.74, F1 score of 0.76 and ROC-AUC of 0.81. It can be stated that the results are effective.
- The Transformer Networks attained a BLEU score of 0.70, accuracy of 0.88 and the AUC-ROC of 0.89. The results indicate that the performance of the model is highly accurate and high AUC-ROC values classify the sentiments effectively.

The results indicate the importance of developing deep learning models when examining sentiment from the social media data. It is clearer that deep learning methods hold promise as useful tools for social work with a focus on community organizing and advocacy. Through the development of these types of models, one can work to ascertain community sentiment more systematically. The research findings can also be useful for social workers and community organizations to encourage the mental health among local population suffering from mental illness.

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