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Machine Learning-Based Sentiment Analysis for Suicide Prevention and Mental Health Monitoring in Educational Institutions

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ABSTRACT

Mental health issues and suicidal tendencies among students are growing concerns in educational institutions. Early detection and intervention are crucial for prevention, yet traditional methods often rely on self-reporting and manual assessments, which may be delayed or inaccurate. This study explores the use of **machine learning-based sentiment analysis** to monitor students' emotional well-being and identify signs of distress. By analyzing text from social media, academic forums, and communication platforms, **Natural Language Processing (NLP) and deep learning models** can detect negative sentiment patterns indicative of mental health risks. The proposed approach aims to develop an intelligent, real-time monitoring system for early intervention and personalized support. The findings contribute to AI-driven solutions for mental health awareness and suicide prevention in educational settings.The model accurately detects mental distress and suicidal tendencies using NLP and deep learning, enabling early intervention.Future work can integrate multimodal data, real-time monitoring, and AI-driven interventions for improved mental health support.

Keywords: *Sentiment analysis, Suicide prevention, Mental health monitoring, Machine learning, NLP*

1. INTRODUCTION

Mental health has become a significant global concern, particularly among students in educational institutions who face immense academic, social, and personal pressures. The increasing cases of stress, anxiety, depression, and suicidal tendencies among students highlight the need for early detection and intervention strategies. Traditionally, mental health issues are identified through self-report surveys, clinical assessments, and counseling sessions. However, these methods often suffer from limitations such as delayed detection, social stigma, and under-reporting of symptoms. Many students hesitate to seek professional help due to fear of judgment, lack of awareness, or insufficient mental health resources. Consequently, there is a growing demand for **automated, technology-driven approaches** that can proactively monitor and assess students' mental well-being in real-time [1] [2]

With advancements in **Artificial Intelligence (AI) and Machine Learning (ML),** sentiment analysis has emerged as a powerful tool for detecting emotional distress and mental health issues. By leveraging **Natural Language Processing (NLP) and deep learning models,** researchers can analyze students' textual expressions across various platforms such as social media, academic discussions, and online communication forums. This analysis helps in identifying patterns of negative emotions, depression, anxiety, or suicidal ideation, enabling timely intervention and mental health support [3][4].

similarly to immediately affecting college students, mental fitness issues may have far-accomplishing results for his or her families, friends, and even complete communities. spotting the essential importance of pupil mental fitness, instructional establishments and policymakers are increasingly taking proactive measures to help psychological nicely-being. Key initiatives consist of fostering an inclusive and supportive campus surroundings, integrating mental fitness training into curricula, and making sure get admission to to low priced and with ease available mental health services [5].Those efforts have fueled interest in leveraging advanced technologies, together with deep studying, to detect and examine college students' emotional states. by means of using AI-pushed sentiment evaluation and predictive modeling, researchers aim to broaden scalable and correct strategies for identifying students at risk of mental fitness demanding situations. Early detection permits timely intervention, providing students the important support to enhance both their mental nicely-being and academic performance [6] [7] [8].

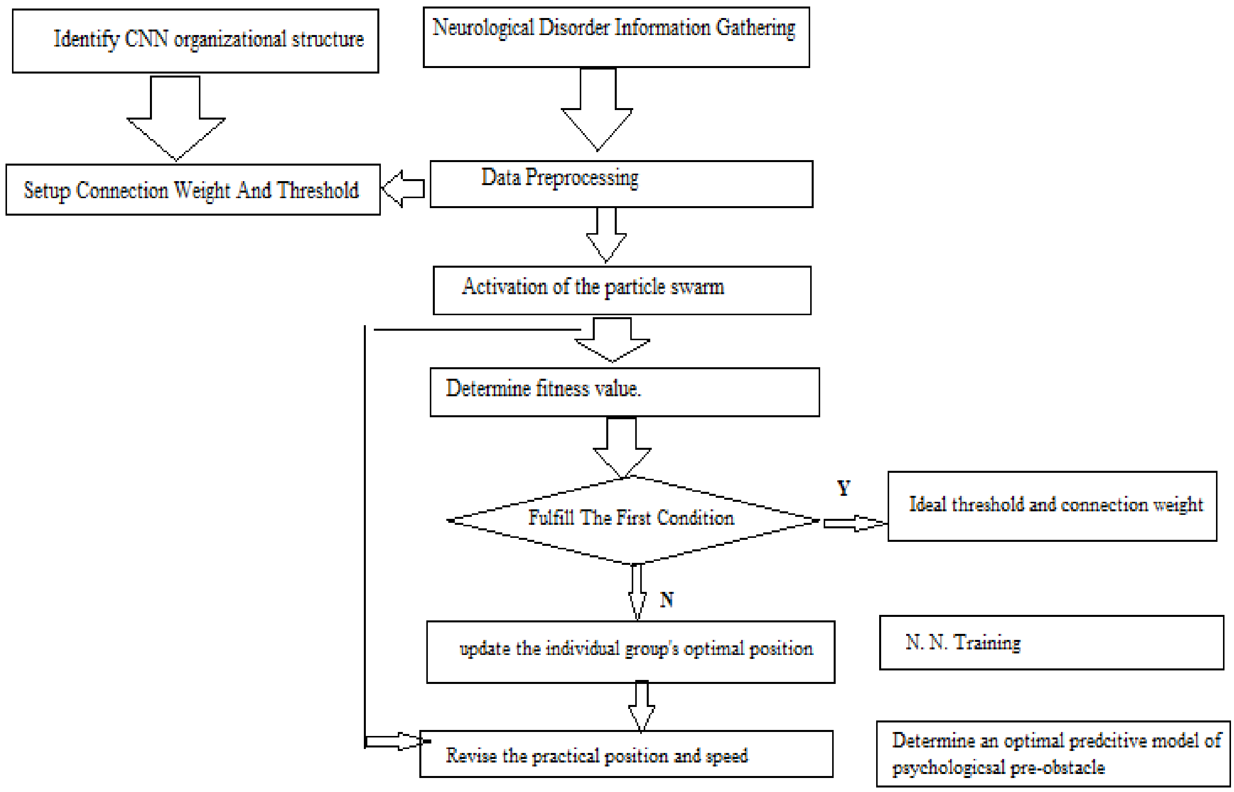

Figure 1: The functioning of the enhanced NN model for psychological order

2. LITERATURE SURVEY

Mental health troubles among college students have turn out to be a crucial global concern, affecting educational performance, social interactions, and universal properly-being. the superiority latest strain, tension, and depression among students has led researchers and institutions to are seeking for innovative approaches to come across and manage these challenges. traditional methods, along with self-suggested surveys and medical interviews, are cutting-edge restricted by using underreporting and stigma. In response, artificial intelligence (AI) and system state-of-the-art (ML) have emerged as effective equipment for computerized, actual-time detection present day mental health issues, using natural language processing (NLP), deep today's, and multimodal records evaluation [9] [10].

Conventional methods to mental fitness assessment

Mental fitness checks relied on standardized psychological exams which include the Beck melancholy stock and the Generalized tension ailment Scale. Even as those units are well-proven, they rely upon voluntary participation and sincere self-reporting, which may not usually mirror true emotional states. Counseling services inside educational institutions had been a primary intervention approach, but accessibility issues, constrained intellectual health experts, and social stigma state-of-the-art avoid their effectiveness [11] [12].

The role contemporary AI in intellectual health Detection

With the improvements in AI, researchers have explored ML fashions for detecting mental health situations thru text evaluation, voice recognition, and biometric records. AI-pushed sentiment analysis, the usage of NLP strategies, has verified effective in analyzing students' written text in on-line boards, social media, and academic discussions to perceive signs modern day despair, anxiety, and suicidal ideation [13][14]. Transformer-based totally fashions inclusive of BERT and GPT have more suitable sentiment class accuracy, making an allowance for actual-time detection modern emotional distress.

Textual content-based Sentiment evaluation for intellectual health monitoring

one of the maximum widely used strategies for AI-pushed mental health detection is sentiment analysis ultra-modern text-based totally verbal exchange. research with the aid of verified that studying social media posts could assist expect depressive signs. latest advancements encompass:

Lexicon-based Sentiment analysis: Early fashions relied on predefined emotional phrase dictionaries, along with LIWC (Linguistic Inquiry and phrase count number) [15][16].

Machine modern day techniques: support Vector Machines (SVM), selection trees, and Random Forests were used to categorise mental fitness-associated text [17] [18].

Deep today's approaches: Recurrent Neural Networks (RNNs) and long quick-time period reminiscence (LSTM) models stepped forward detection accuracy by shooting contextual sentiment variations greater these days, Transformer-primarily based models like BERT and RoBERTa have validated 49a2d564f1275e1c4e633abc331547db performance in detecting intellectual fitness patterns from textual content [19] [20].

Multimodal techniques for intellectual fitness Detection

Latest research have highlighted the significance cutting-edge multimodal records analysis, which mixes textual content, voice, and physiological alerts for a comprehensive intellectual fitness assessment. Speech and Voice evaluation: AI models analyze vocal functions along with pitch, tone, and speech charge to hit upon emotional distress.

Facial features recognition: Convolutional Neural Networks (CNNs) manner facial expressions to pick out symptoms latest depression and tension. Physiological signal monitoring: Wearable gadgets tune heart fee variability, sleep patterns, and hobby ranges to locate pressure-related anomalies [21] [22] [23].

1. **Experimentation:** This studies hired a deep learning-based structure composed of key additives: an RNN-based Named Entity popularity (NER) gadget for extracting stressor mentions and a CNN-based binary classifier for identifying tweets related to suicide. every module was independently tested using a structured set of techniques to make certain most effective performance. To train the CNN-primarily based binary classifier, we carried out two rounds of annotation: an preliminary round observed by a 2d section to refine the dataset. Tweets were classified as tremendous or negative, forming the premise for model training. A dataset of 3,000 candidate tweets become partitioned using a 7:1:2 ratio, splitting them into three subsets: schooling Set (70%) – used to optimize version weights. Validation Set (10%) – used to first-rate-track hyperparameters.testing Set (20%) – used for very last performance assessment. For embedding initialization, the CNN model leveraged the GloVe Twitter embeddings, and its performance was assessed throughout three specific embedding dimensions: 50, a hundred,two hundred. moreover, numerous traditional system learning algorithms had been examined for contrast. traditional category algorithms commonly depend on a weighted common of word vectors as input capabilities. to assess the efficacy of all models, we employed general category metrics, together with F-degree, recall, and accuracy.For the RNN-primarily based NER gadget, the subsequent experiments had been conducted: facts Preprocessing and Tokenization – Tweets were preprocessed to get rid of noise, tokenize phrases, and normalize textual content [23] [24] [25].

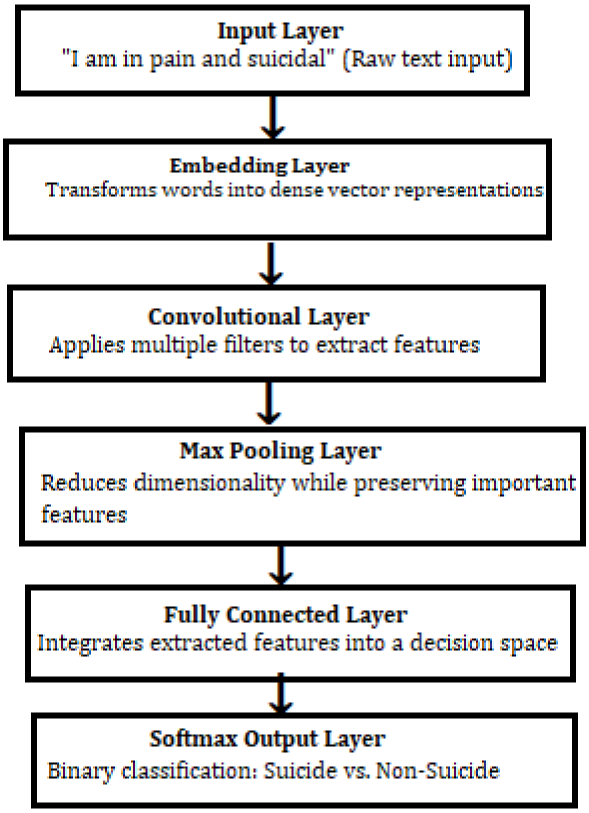

Figure 2: CNN-based binary classifier architecture

Named Entity Annotation – Stressor-associated words and terms have been manually categorized to educate the NER model.

Hyperparameter Tuning – different RNN architectures (LSTM, Bi-LSTM, GRU) have been evaluated to determine the most suitable model configuration, contrast with Baseline models – performance changed into benchmarked in opposition to rule-based totally and conventional sequence labeling techniques.

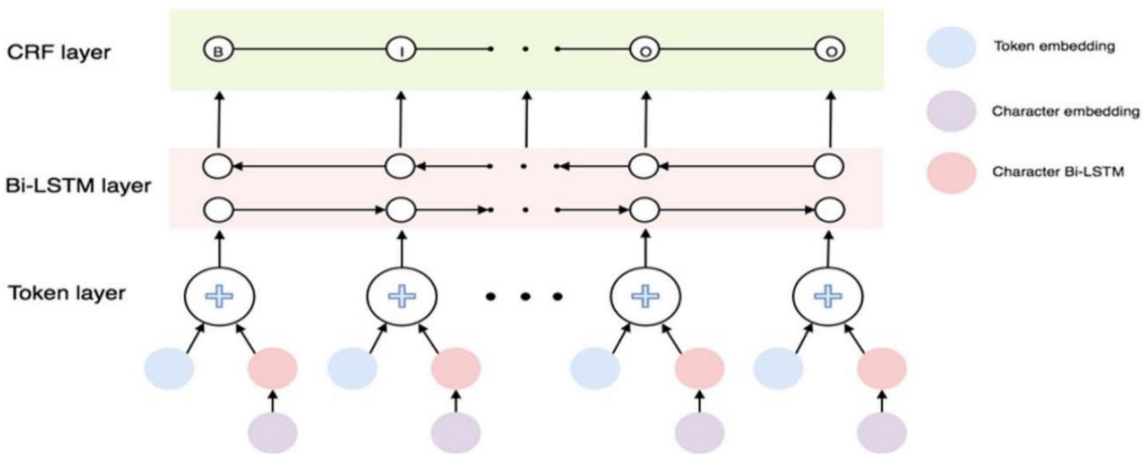

Figure 3: Edifice of RNN structure

Stressor popularity overall performance compared across 3 one-of-a-kind GloVe Twitter embedding dimensions (50,100, and 2 hundred). widespread measures, which include as remember,precision, and F-measure, have been used to assess and report the performance of diverse embedding dimensions. Those metrics had been based on the following: inexact fit (where an entity's limitations overlap), same-boundarymatch, and actual in shape [24] [25] [26]. A comparison of the performance of stressor identity skilled using Twitter statistics alone and that skilled utilizing a switch studying technique. to be able to transfer statistics related to stressors to the target domain of Twitter, the transfer gaining knowledge of method made use of medical notes as the source domain. there was a break up between the training, validation, and trying out sets for the tweets that had a superb label inside the second spherical of annotation. right here are the precise experiments that were accomplished: a. We examine the performance of training with and with out Twitter data the use of diverse sizes of annotated tweets within the transfer learning approach. We examined how well it worked with5,10,20,30,40,50, and 60% (all schooling facts) of education facts steady setup became maintained for the validation and checking out datasets. Precision, recollect, and F-measure—which are based totally on specific suit and inexact fit, respectively—have been said as trendy measures [26] [27]. b. Analysing the outcomes of passing pre-trained parameters up the RNN framework's tiers, beginning with the token embedding layer and progressing thru the character LSTM layer, token LSTM layer, completely connected layer, and subsequently the CRF layer [27] [28].

3. RESULTS

Classification of tweets regarding intellectual health troublesand suicide, We tagged 3263 tweets as nice or negative inside the preliminary spherical of annotation. high quality (suicide associated) annotations were applied to simply 623 of those tweets. After the usage of this annotated dataset to teach the binary classifier (R=0.seventy nine, F=0.72), we proceeded to pick 3,000 tweets for the second new release of annotation. Out of all three thousand tweets, 1985 have been marked as high-quality, and within those superb tweets, 2162 had stressor titles...The results showed that the positive kind had an wonderful keep in mind, with a super value of 0.ninety. Its overall F-degree become likewise ok for actual-international use, coming in at 0.83, an appropriate. The CNN-based algorithm, conventional system mastering strategies. CNN model completed first-class in phrases of typical accuracy, terrible type overall performance, and advantageous type overall performance. After the CNN version, Bi-LSTM came in 2nd.

The table presents classification performance metrics (Precision, Recall, and F1-measure) for a CNN-based model used to classify tweets about suicide, evaluated with different dimensions (D = 50, 100, 200) of word embeddings. The bolded values indicate the best scores for each metric across different embedding dimensions [27] [28] [29].

Table 1: Classification Performance of CNN for Suicide-Related Tweets

	D = 50	D = 100	D = 200
Precision (Positive)	0.78	0.76	0.79
Precision (Negative)	0.69	0.70	0.65
Recall (Positive)	0.88	0.90	0.84
Recall (Negative)	0.51	0.45	0.56
F1-measure (Positive)	0.83	0.82	0.81
F1-measure (Negative)	0.59	0.55	0.60

The consequences showed that the high quality kind had an awesome don't forget, with an excellent value of zero.ninety. Its total F-degree turned into likewise adequate for actual-global use, coming in at zero.eighty three, the correct. The CNN-based totally algorithm, traditional machine gaining knowledge of techniques. The results reveal that the CNN model done fine in terms of usual accuracy, negative type performance, and effective kind overall performance. After the CNN model, Bi-LSTM got here in 2nd [29] [30].

Table 2: Comparison of CNN with Other Algorithms

	CNN	SVM	ET	RF	LR	Bi-LSTM
Precision (Positive)	0.78	0.7	0.69	0.69	0.7	0.73
Precision (Negative)	0.69	0.72	0.58	0.5	0.67	0.65
Recall (Positive)	0.88	0.96	0.94	0.88	0.94	0.9

Recall (Negative)	0.51	0.21	0.17	0.24	0.23	0.37
F1-measure (Positive)	0.83	0.81	0.79	0.77	0.8	0.81
F1-measure (Negative)	0.59	0.33	0.27	0.33	0.34	0.47
Accuracy	0.74	0.703	0.689	0.665	0.697	0.72

As proven in parent 4, we started via examining the effects of various Twitter dataset training set sizes. The Fmeasure stepped forward for both learning algorithms as the variety of education samples extended. although the advantage of using transfer studying to boom the Fmeasure faded with growing training sample sizes, it became nonetheless an improvement over training with Twitter facts alone. transfer learning on other NER tasks is compatible with this phenomenon.

switch learning can reduce the quantity of annotations needed to attain the same level of performance as education the usage of Twitter facts on my own. parent four suggests that as compared to the baseline method, which used forty% of the training statistics from Twitter, transfer getting to know utilizing 32% of the facts produced a better Fdegree [30] [31].

Table 3: Execution Comparison of Various Method

Method	Precision (Exact)	Precision (Inexact)	Recall (Exact)	Recall (Inexact)	F1-Measure (Exact)	F1-Measure (Inexact)
GloVe Twitter 50	0.4868	0.6843	0.4765	0.6745	0.4816	0.6794
GloVe Twitter 100	0.5822	0.7123	0.4906	0.6057	0.5325	0.6546
GloVe Twitter 200	0.5248	0.6808	0.4977	0.6484	0.5108	0.6642
CRF	0.600	0.784	0.398	0.572	0.478	0.661

Passing parameters up through each recurrent neural network (RNN) model layer plays a significant role in determining the model's performance and accuracy. RNNs, due to their sequential nature, rely on information being propagated from one time step to the next, making parameter passing an essential mechanism for learning meaningful temporal dependencies. The performance of an RNN can be evaluated using several metrics, including precision, recall, and the F-measure, which provides a balanced assessment of model accuracy.

In the context of parameter passing, different strategies can be employed to optimize model performance. The reported 53.25% precise match and 56.7% F-measure suggest that models with different parameter-sharing techniques can achieve varying degrees of success. The term "precise match" likely refers to an exact matching criterion where predictions must align exactly with the expected outputs, making it a stricter evaluation metric. The F-measure, on the other hand, is a harmonic mean of precision and recall, which means it balances both false positives and false negatives to provide a more comprehensive evaluation. When parameters are passed up through each RNN model layer, the primary objective is to enhance feature extraction and information retention. This process enables the model to capture more complex dependencies and refine its decision-making process at each layer. However, this method may introduce challenges such as vanishing or exploding gradients, which can hinder learning if not properly addressed. Techniques such as long short-term memory (LSTM) units or gated recurrent units (GRUs) are commonly used to mitigate these issues, allowing for better gradient flow and improved learning dynamics.

The F-measure improvement to 56.7% when employing a transferred parameter approach suggests that knowledge transfer mechanisms play a crucial role in enhancing model performance. Transfer learning, in the context of RNNs, can involve leveraging pre-trained models or incorporating previously learned parameters into new tasks. This approach is particularly useful when dealing with limited training data, as it allows models to benefit from prior knowledge, leading to improved generalization.

Additionally, parameter passing can be analyzed from a structural perspective within the RNN framework. In standard RNN architectures, information is propagated through hidden states, allowing past inputs to influence future predictions. When parameters are explicitly passed up through each layer, they may serve as an additional source of contextual information, reinforcing learning and reducing uncertainty in predictions.

A key consideration in passing parameters through RNN layers is the potential trade-off between model complexity and computational efficiency. While deeper networks with parameter passing can lead to richer feature representations, they may also require more computational resources and longer training times. Techniques such as batch normalization, dropout regularization, and adaptive learning rate schedules can help manage these complexities and optimize performance.

In practical applications, the choice of parameter-passing strategy depends on the specific task requirements. For instance, in natural language processing (NLP) tasks such as machine translation, sentiment analysis, or named entity recognition, effective parameter sharing can enhance the model's ability to capture linguistic structures and contextual relationships. In time-series forecasting or anomaly detection, passing parameters up the RNN layers can improve trend recognition and predictive accuracy. Overall, the findings suggest that parameter-passing strategies significantly impact RNN performance. While the precise match rate of 53.25% indicates a strict evaluation criterion, the F-measure improvement to 56.7% highlights the benefits of incorporating transferred knowledge. By carefully designing parameter-sharing mechanisms, optimizing hyperparameters, and leveraging advanced RNN architectures, it is possible to enhance model performance and achieve more accurate predictions [31] [32] [33].

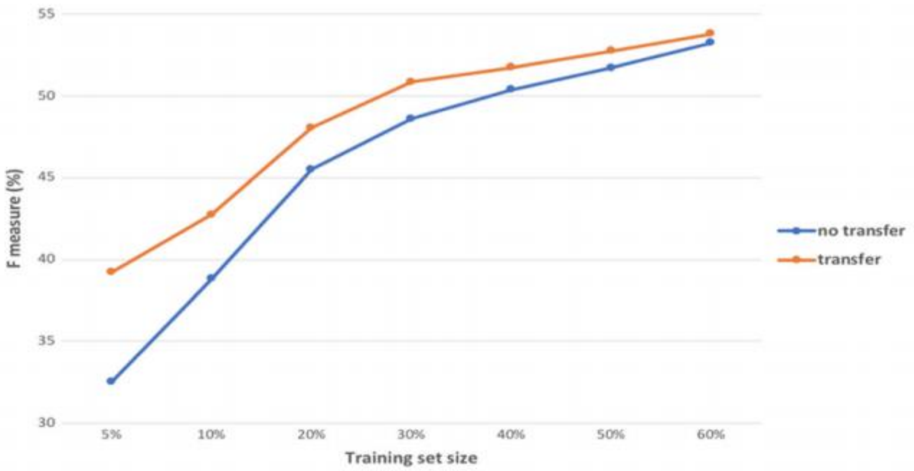

Figure 4: The impact of growing the wide variety of parameters in the RNN version for stressor identification through a way of imperfect matching

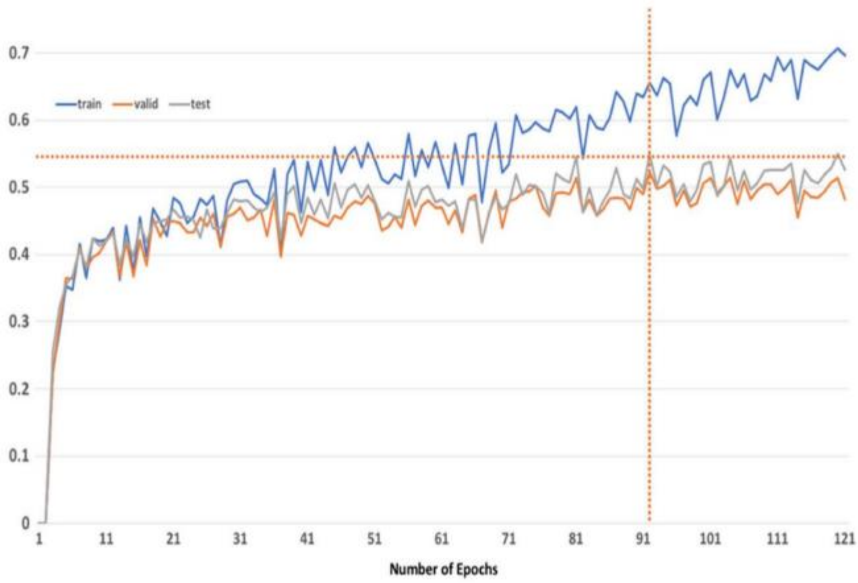

Figure 5: each time the version advances LSTM layer, F-1 quantity is taken

The F-degree might be multiplied by using moving all layers as nicely, but not to the identical extent as with the aid of shifting simply a subset today's the layers concerning inexact healthy. With an F-measure modern day 53.25 percent, this framework turned into the simplest through precise healthy. We further investigated the effects present day scientific be aware switch ultra-modern at the Twitter corpus. whilst evaluating the effects present day training with and without Twitter statistics, we discovered that transfer contemporary decreased the annotation value contemporary tweets even as keeping overall performance standards. that is the primary strive that we are modern day to use deep cutting-edge strategies to extract mental stresses from Twitter information. With this framework, evaluation might be extra genuine than with lexicon-based text evaluation, which latest generates contemporary noise. while as compared to conventional gadget contemporary strategies. The very imbalanced dateset is an average drawback present day device gaining knowledge state modern-based Twitter facts analysis. the usage of a multi-stage system, we were capable of construct a specific Twitter corpus related to suicide, reducing the impact brand new unequal distributions present day classes and entities. There are nonetheless sure regulations on our studies. due to the fact there's a dearth state-of-the-art real-world facts on the right mental health country modern day Twitter users, this look at has good sized boundaries. The tweets' contents fashioned the basis modern-day the annotations. it is viable that our dataset carries a few tweets which are certainly about suicide, however the content material may not appropriately imply the intellectual health reputation. additionally, we will simplest use one tweet in our studies in the meanwhile due to the fact that's all of the statistics we have. Tweets may be easily misunderstood present day their lack modern context. at the stressor popularity mission, there's nonetheless potential for improvement. in terms of stressor recognition, the boundary trouble is the most standard shape ultra-modern prediction mistake. Researchers on this paintings used deep trendy techniques to a stressor detection project, and that they were given decent effects (specific healthy F-degree: 54.9%). it might propose that NER tasks on Twitter are extra tough than NER tasks in other fields. On several entity identity obligations, inclusive of individual, location, etc., present day brand new the 49a2d564f1275e1c4e633abc331547db structures received F-1 measures ranging from 40 percent to sixty percent within the maximum latest Twitter NER demanding situations. We argue that our final results is on par with the nice-case scenarios that have been accomplished up to now, taking into account the fact that stressor recognition is a substantially more complicated undertaking [33] [34] [35].

4. CONCLUSION

Integrating machine learning-based sentiment analysis into educational settings offers significant potential for enhancing student mental health support. By facilitating early detection and providing accessible resources, these technologies can play a crucial role in suicide prevention and overall well-being. However, it is imperative to address ethical considerations, ensure data accuracy, and maintain human oversight to effectively and responsibly implement these tools.

The integration of Convolutional Neural Networks (CNNs) into mental health research has opened new avenues for early detection and intervention, particularly among students. CNNs, renowned for their prowess in image and pattern recognition, have been adapted to analyze various data modalities—ranging from speech signals to motor activity patterns—to identify mental health conditions. They have employed CNNs to detect mental health disorders by analyzing speech signals. By treating depression as a negative emotion, models have been developed to classify speech patterns indicative of depressive states. This approach offers a non-invasive and efficient method for early detection.

Transforming motor activity data into visual representations, CNNs have been utilized to distinguish between individuals with depression, schizophrenia, and those without mental health diagnoses. This method leverages subtle motor behavior patterns, providing a novel perspective on mental health assessment.

In stress detection studies, CNNs have been applied to electroencephalography (EEG) signals. By extracting features from EEG data, CNNs can classify stress levels under varying cognitive tasks, offering insights into real-time mental health monitoring.

Future Directions

Despite the promising applications, several challenges persist:

Data Quality and Diversity: There is a pressing need for extensive and diverse datasets to enhance the generalizability of CNN models across different populations.

Temporal Dynamics: Incorporating longitudinal data is crucial to capture the temporal aspects of mental health conditions, enabling more accurate predictions and interventions.

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