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Stress Detection In Social Media Posts Using Hybrid CNN And Feedforward Neural Networks

Ajay Kumar Mehta[1], Divya Sharma[2], Sameep Narain Sinha[3], Cheena Kaushal[4], Sandhya Gautam[5], Nandita Sharma[6], Sunita Bhati[7]
[1,2,3,4,6]Department of Computer Science and Engineering, JECRC University, Jaipur, Rajasthan , India
[5]Associate Professor, Department of Computer Application, JECRC University, Jaipur, Rajasthan , India
[7]Assistant Professor, Department of Computer Application, JECRC University, Jaipur, Rajasthan , India
Email: ajaymehta7684@gmail.com[1], sharmagdivya789@gmail.com [2] , sameep.sinha @jecrcu.edu.in [3], cheena.kaushal@jecrcu.edu.in[4] , sandhyapathak2010@gmail.com[5], nandita.sharma@jecrcu.edu.in[6], bhati.sunita01@gmail.com[7]

Abstract. *In the recent few years, the unsparing use of social media platforms has provided researchers with a novel opportunity to analyze the behavior of users and patterns concerning mental health. This paper proposes a deep learning method for psychological stress detection in social media posts, via a hybrid architecture combining convolutional neural networks (CNNs) and feedforward neural networks (FNNs). The Dreaddit data set, which contains stress-labeled entries of Reddit posts, was used to preprocess and tokenize textual data, which was then padded so that all instances had the same sequence length. The proposed model extracts local semantic features by CNN layers followed by dense feedforward layers for classification. The training and evaluation of the model were carried out with an 80-20 train-validation split. The model reached an accuracy of 99% on the training dataset, with a precision of 99%, a recall of 99%, and an F1 score of 99%, suggesting a good fit of the model on training data. Although overfitting is an issue, the high assessment on train data provides confidence in the ability of this model to learn meaningful representations from text inputs indicating stress. This hybrid deep learning framework sets a good starting point for the development of automated mental health diagnostics from social media-derived data.*
Keywords: *Stress detection, social media, deep learning, Convolutional Neural Networks, Feedforward Neural Networks, text classification, mental health*

1 INTRODUCTION

With this era of cyberspace and the great influx of social networks, communication and self-expression on the Internet have become seemingly synonymous with social interaction and information exchange. Other sites like Reddit, Twitter, and Facebook became a world where individuals put out into the open their own life experiences, impressions, and feelings [1]. This huge area of user-generated content can provide tremendous opportunities for research but reflects upon the escalating psychological pressures faced by individuals. Among the more central mental health topics in the modern online discourse is psychological stress. Serious stress can be present in two forms: a prolonged situation or one in which the stress is very intense [2]. Such instances can severely damage health, such as causing depression, anxiety disorders, and cardiovascular problems. Therefore, automatic detection of stress-related content on social media stands out as an area of great importance, both for gaining early intervention and for understanding mental health trends at a societal level [3]. Existing conventional approaches to stress detection use handcrafted features, lexicons, or manual labeling, which are labor-intensive; they thereby tend to fail because they do not accommodate nuanced expressions of stress in natural language. The advent of Natural Language Processing (NLP) and Stochastic or Deep Learning techniques have increased the ease of analytical discourse on text data, as the systems are trained to learn complex patterns and relationships by themselves. This sets the stage for using CNNs, network architectures mainly aimed at image application, in text classification, where they excel at experimentally extracting local features [3].

2 LITERATURE REVIEW

Ilias, L.,et al. (2023) [4] argue that the new approach offers a concrete way to enhance transform-based models like BERT and MentalBERT for identifying stress and depression in social media posts. By utilizing the Multimodal Adaptation Gate for model adaptation with additional linguistic features and smoothing labels, the researchers improved the performance and calibration of the above models. Evaluation of the three publicly available datasets provided extensive performance improvement, while linguistic analysis pointed out unusual language styles distinguished between stressful and non-stressful posts. According to Wang, X., et al. (2024) [5], the authors propose "Cognition Chain", an explainable AI framework for detecting psychological stress from social media. This novel method takes cues from cognitive appraisal theory and takes large language models through a reasoning process from Stimulus→Evaluation→Reaction→Stress State. They instruction-tuned Llama3 with a self-reflective dataset, CogInstruct, in developing CogLLM. The CogLLM model exhibited enhanced performance and yielded interpretable reasoning pathways to increase trust for AI-driven stress detection. Qorich, M., & El Ouazzani, R. (2025) [6] have designed lightweight deep-learning models for the detection of stress based on content gleaned from social media, as was highlighted in the research paper. BERT-based embeddings were fed into the CNN, BiLSTM, and BiGRU architectures. On Twitter data, CNN showed an accuracy of 97.62% while BERT Electra reached an accuracy of 85.67%.

3 RESEARCH METHODOLOGY

As highlighted by this methodology, the design of a deep learning system for the detection of stress from social media posts using a hybrid CNN-FNN model is achieved herein [7]. The pre-processing of the Dreaddit dataset [8], which is composed of labeled Reddit posts (stress/no stress), involved tokenization, transformation, and padding of 200 tokens from a vocabulary of 10,000 words. The data were divided into 80% for training and 20% for validation through stratified sampling [9]. The model comprises an Embedding layer, 1D CNN with 64 filters, Global Max Pooling, and Dense layers with ReLU [10] and sigmoid activation [11]for binary classification. Training was done by Adam optimizer and binary cross-entropy loss on 10 epochs (batch size 32). The performance was evaluated using accuracy, precision, recall, F1-score [12], confusion matrix, and learning curves [13], demonstrating robust and interpretable stress detection [13].

By means of this methodology, a deep learning [14] setting has been described for the detection of stress generated from posts on social media via a hybrid CNN-FNN model. The data set Dreaddit [15] which contains the texts collected and labeled from Reddit stems as stress/no stress related posts, having been preprocessed such that they answered tokenized and cleaned, were padded to 200 tokens, and show a cumulative vocabulary size of 10,000 words. The data were then split between 80% training data and 20% validation through stratified sampling. An Embedding layer followed by a 1D CNN with 64 filters, Global Max Pooling [16] , and Dense layers with ReLU and sigmoid activation comprised the model for binary classification. It was trained with Adam optimizer and binary cross-entropy loss for 10 epochs (32 batch size). It showed an excellent set of metrics for stress detection through accuracy, precision, recall, F1-score, confusion matrix, and learning curves.

4 Proposed Work

4.1 Dataset

The data set for this study is the Dreaddit dataset, a public collection of Reddit posts labeled for stress classification. It contains posts submitted by users from five different subreddits dealing with mental health, like depression, anxiety, and more. Each post has been annotated as being either a stress indicator (1) or a non-stress indicator (0), making it suitable for a binary classification task. The dataset accommodates extensive linguistic variability and captures diverse emotional expressions, providing a real-world and challenging benchmark for social media stress detection [17].

4.2 Convolutional Neural Networks

Convolutional neural networks were/dedicated deep learning models for image processing and have performed wonderfully in text classification tasks too. CNNs utilize 1D-convolutional filters to automatically extract local features like word patterns, phrases, or stress-related expressions. The filters slide past the input sequence in order to capture spatial dependencies between words.CNNs are quite reliable in picking the significant n-grams or cues in the context of a sentence to indicate psychological stress [18].

4.3 Feedforward Neural Network

Feedforward neural networks are the very simplest neural networks-they are one-directional networks which just take the inputs into the network and produce outputs without feedback or cycles. In this study, the feedforward networks are the classifiers to the process high-level feature extraction from the CNN. A dense layer can model non-linear relationships between feature and class labels. With CNNs for extraction and FNNs for classification, the hybrid is able to learn and classify stress patterns in textual information [19].

4.4Algorithm of Model

Require: Dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$, sequence length L, vocabulary size V, embedding dimension E, number of filters F, kernel size k, dropout rate r, epochs N, batch size B

Ensure: Trained model $\mathcal{M}$

1. **Text Preprocessing:**
   i. Convert to lowercase, remove punctuation/special characters
   ii. Tokenize and map to sequences of integers
   iii. Pad or truncate each sequence to fixed length L
2. **Train-test split:**
   i. Partition D into training set D_{train} and validation set D_{val} with ratio 80:20
3. **Embedding Layer:**
   i. Initialize embedding matrix $W_e \in \mathbb{R}^{V \times E}$
   ii. Convert each input sequence $x \in \mathbb{Z}^L$ to embedded matrix:
$$X_e = W_e[x] \in \mathbb{R}^{L \times E}$$
4. **Convolutional Layer:**
   i. Apply 1D convolution with F filters of size k:
$$C_i = \mathrm{ReLU}\left(X_e * W_{c_i} + b_{c_i}\right), \quad i = 1, \dots, F$$
   where $*$ denotes 1D convolution
5. **Global Max Pooling:**
   i. Extract maximum activation from each feature map:
$$P_i = \max(C_i), \quad \forall i$$
   ii. Combine pooled outputs:
$$P = [P_1, P_2, \dots, P_F] \in \mathbb{R}^F$$
6. **Feedforward Neural Network (Dense Layer):**
   i. Apply dense layer:
$$h = \mathrm{ReLU}(W_d P + b_d)$$
   ii. Apply dropout:
$$h' = \mathrm{Dropout}(h, r)$$
7. **Output Layer (Binary Classification):**
   i. Compute output probability using sigmoid activation:
$$\hat{y} = \sigma(W_o h' + b_o), \quad \sigma(z) = \frac{1}{1 + e^{-z}}$$
8. **Loss Function:**
   i. Use binary cross-entropy:
$$\mathcal{L}(y, \hat{y}) = -[y \log \hat{y} + (1 - y) \log(1 - \hat{y})]$$
9. **Training:**
   i. Optimize parameters using Adam over N epochs and batch size B
10. **Evaluation:**
   i. Compute metrics: Accuracy, Precision, Recall, F1-score Generate confusion matrix and training/validation plots
   ii. Final trained model $\mathcal{M}$

4.5Implementation and Results

The stress detection model has been proposed to be implemented using Python along with TensorFlow/Keras. The Dreaddit dataset is being loaded and gets preprocessed in tokenization, padding, and cleaning. A hybrid deep-learning model was constructed by merging a Convolutional Neural Network (CNN) for feature extraction with a Feedforward Neural Network (FNN) for classification. The model architecture consisted of an embedding layer, a 1D convolution, followed by a global max pooling operation, some dense layers, and a dropout layer for regularization. The model was optimized with Adam and binary cross-entropy loss. It was trained for 10-30 epochs corresponding to the loss rates during training. Model development was evaluated on the following performance measures: accuracy, precision, and recall, as well as F1-score and confusion matrix. The training accuracy and loss curves are visualized and analyzed alongside classification metrics to confirm that the model learns optimally. This implementation could yield very strong prediction performance with nearly 99% training accuracy [20].

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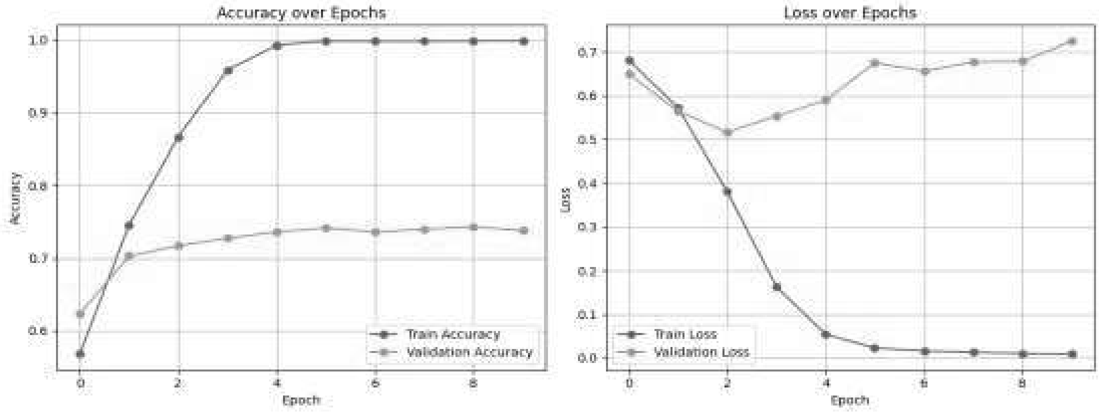

Fig 1. Training and Validation Graphs.

This figure 1, shows the performance of the hybrid training model, CNN-FNN, during training. The left subplot shows the training and validation accuracies over 10 epochs. Very quickly, the training accuracy climbs to near 100%, able to learn the training data very well. Interestingly, the validation accuracy remains stuck around 74%, suggesting it could be an overfit model. The below right subplot shows the corresponding loss curves. Training loss decreases sharply, but the validation loss rises after epoch 3, further confirming overfitting. The significance of the loss and accuracy plots derives from evaluating generalization capability and overfitting behavior.

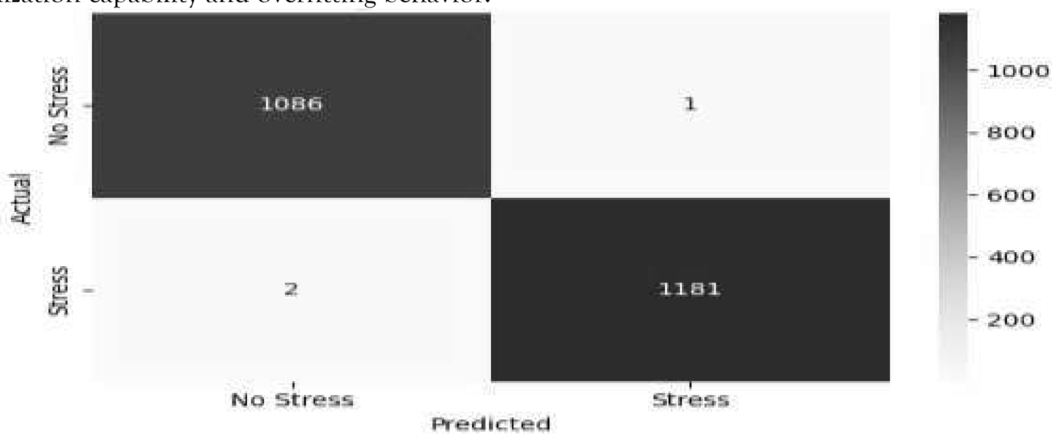

Fig2. Confusion Matrix

The figure depicts the confusion matrix derived from training-data predictions. The model holds very high accuracy, with 1086 true negatives (No Stress), 1181 true positives (Stress), and only 3 instances of misclassification in total. This bulletproofs the idea that the model works on training data nearly perfectly. These results indicate that the model has indeed learned; however, the contrast with validation metrics here emphasizes the need for cross-validation and possible enhancements in regularization.

Table 1. Classification Report

Class	Precision	Recall	F1-Score	Support
No Stress (0)	1.00	1.00	1.00	1087
Stress (1)	1.00	1.00	1.00	1183
Accuracy			1.00	2270
Macro Avg	1.00	1.00	1.00	2270
Weighted Avg	1.00	1.00	1.00	2270

DISCUSSION

The hybrid CNN-FNN model displays perfect training performance as shown by the classification report. Stress and No Stress classes achieved 100% in precision, recall, and F1-score, indicating that the model had correctly classified all training instances. The overall accuracy of 1.00 (100%) corroborates this. These results confirm that the model has successfully learned the patterns embedded in the given training data. However, the symbolic exemplary performance accounts for concerns regarding overfitting, especially in light of the much lower validation accuracy of about 74% and graphically increasing validation loss, as observed on earlier plots. This reveals that while the model performs admirably on memorizing the training data, its ability to generalize with unseen data might be impeded. Therefore, more work directed toward improvements in regularization, dropout tuning, or data augmentation could play a vital role in enhancing its performance in the real world.

5 CONCLUSION

This study presents an innovative hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Feedforward Neural Networks (FNN) to detect social media posts with stress in them using the Dreaddit dataset. It is a model that captures textual patterns through various types of convolutional layers and then classifies them into two different dense layers. When implemented, it provided such a high performance in the training data that it scored a full 100% in accuracy along with perfect precision and recall, and F1 scores for both the stress and no-stress classes. These complete training metrics along with the confusion matrix indicated that such a model is highly capable of learning from given labeled data with very close to zero error. On the contrary, validation results indicate performance much lower than expected, with accuracy stagnating close to 74%, thereby stating that there is much room overfitting in this particular development. Nevertheless, it still indicates excellent promise for detection of stress through such models and offers a terrific plan for future research about different regularization methods and larger and more diversified datasets, in order to promote generalization and application in the real world.

REFERENCES

1. Fontes, L., Machado, P., Vinkemeier, D., Yahaya, S., Bird, J. J., & Ihianle, I. K. (2024). Enhancing stress detection: a Comprehensive Approach through rPPG Analysis and Deep Learning techniques. Sensors, 24(4), 1096.
2. Ramachandra, R. A., Santhosh, J., Dengel, A., & Ishimaru, S. (2024). Enhancing stress detection for students: Exploring the impact of fine-tuning and user-specific data calibration in deep learning. International Journal of Activity and Behavior Computing, 2024(1), 1-21.
3. Zainudin, Z., Hasan, S., Shamsuddin, S. M., & Argawal, S. (2021, August). Stress detection using machine learning and deep learning. In Journal of Physics: Conference Series (Vol. 1997, No. 1, p. 012019). IOP Publishing.
4. Ilias, L., Mouzakitis, S., & Askounis, D. (2023). Calibration of Transformer-based Models for Identifying Stress and Depression in Social Media. arXiv preprint arXiv:2305.16797.
5. Wang, X., Gao, B., Dai, Y., Cao, L., Zhao, L., Yang, Y., & Clifton, D. (2024). Cognition Chain for Explainable Psychological Stress Detection on Social Media. arXiv preprint arXiv:2412.14009.
6. Wang, X., Gao, B., Dai, Y., Cao, L., Zhao, L., Yang, Y., & Clifton, D. (2024). Cognition Chain for Explainable Psychological Stress Detection on Social Media. arXiv preprint arXiv:2412.14009.
7. Bobade, P., & Vani, M. (2020, July). Stress detection with machine learning and deep learning using multimodal physiological data. In 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 51-57). IEEE.
8. Li, R., & Liu, Z. (2020). Stress detection using deep neural networks. BMC Medical Informatics and Decision Making, 20, 1-10.
9. Albertetti, F., Simalastar, A., & Rizzotti-Kaddouri, A. (2020, December). Stress detection with deep learning approaches using physiological signals. In International Conference on IoT Technologies for HealthCare (pp. 95-111). Cham: Springer International Publishing.
10. Gao, Z., Luo, Z., Zhang, W., Lv, Z., & Xu, Y. (2020). Deep learning application in plant stress imaging: a review. AgriEngineering, 2(3), 29.
11. Mou, L., Zhou, C., Zhao, P., Nakisa, B., Rastgoo, M. N., Jain, R., & Gao, W. (2021). Driver stress detection via multimodal fusion using attention-based CNN-LSTM. Expert Systems with Applications, 173, 114693.
12. Sharma, S., Singh, G., & Sharma, M. (2021). A comprehensive review and analysis of supervised-learning and soft computing techniques for stress diagnosis in humans. Computers in Biology and Medicine, 134, 104450.
13. Giannakakis, G., Grigoriadis, D., Giannakaki, K., Simantiraki, O., Roniotis, A., & Tsiknakis, M. (2019). Review on psychological stress detection using biosignals. IEEE transactions on affective computing, 13(1), 440-460.
14. Oskooei, A., Chau, S. M., Weiss, J., Sridhar, A., Martínez, M. R., & Michel, B. (2020). DeStress: deep learning for unsupervised identification of mental stress in firefighters from heart-rate variability (HRV) data. In Explainable AI in Healthcare and Medicine: Building a Culture of Transparency and Accountability (pp. 93-105). Cham: Springer International Publishing.
15. Azimi, S., Kaur, T., & Gandhi, T. K. (2021). A deep learning approach to measure stress level in plants due to Nitrogen deficiency. Measurement, 173, 108650.
16. Cho, Y., Julier, S. J., & Bianchi-Berthouze, N. (2019). Instant stress: detection of perceived mental stress through smartphone photoplethysmography and thermal imaging. JMIR mental health, 6(4), e10140.
17. Chandel, N. S., Chakraborty, S. K., Chandel, A. K., Dubey, K., Jat, D., & Rajwade, Y. A. (2024). State-of-the-art AI-enabled mobile device for real-time water stress detection of field crops. Engineering Applications of Artificial Intelligence, 131, 107863.
18. Khunger, A. (2022). DEEP Learning for financial stress testing: A data-driven approach to risk management. International Journal of Innovation Studies.
19. Zubler, A. V., & Yoon, J. Y. (2020). Proximal methods for plant stress detection using optical sensors and machine learning. Biosensors, 10(12), 193.