National College of Ireland

A Deep Learning Framework for Stress and Depression Detection

MSc Research Project
MSc in Data Analytics

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MSc Project Submission Sheet

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Student Name:	Mohammad Nihaal Naazim		
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A Deep Learning Framework for Stress and Depression Detection

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Abstract

Stress and depression are some of the leading mental health disorders affecting the society in today's world. These conditions are still a major concern to public health, thus there is a need for prevention and control measures. This work focuses on training Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) on stress and depression public datasets to predict mental health outcomes. CNNs were deployed on structured data for extracting spatial features while, RNNs analyzed temporal features extracted from behavioral measurements. The results show that RNNs exceeded CNNs, achieving an impressive 99% accuracy in stress prediction and 79% accuracy in depression analysis. Meanwhile, CNNs demonstrated strong performance in classifying structured data. RNNs were more effective in processing sequential data and handling finer distinctions in categorization. These findings underscore the potential of deep learning to enhance traditional analytical methods and provide scalable, efficient tools for mental health assessment. Future research will focus on integrating multimodal data and developing hybrid models to further improve the models' performance and applicability in real-world scenarios.

1 Introduction

Depression and stress are the two conditions that are most common in the world today, cutting across age limits and socioeconomic status. Based on the WHO, these conditions rank in the top 10 non-communicable diseases that cause disability in human beings and affect over 280 million individuals suffering from depression and 264 million people affected by anxiety disorders. In spite of the fact that the primary symptoms of the above conditions are often detected in childhood, timely diagnosis and intervention are critical to reduce the impact of these diseases; however, the use of other widespread models of clinical assessment, including observational assessment by a clinician and, questionnaires filled in by the patient, is subjective, time-consuming, and not scalable (Ahmed et al., 2020).

Recently, Machine Learning and Deep Learning have been seen as revolutionary approaches in diagnostics of Mental Health as these approaches have handling capacity of large volumes of data and pattern detection. Such technologies provide tremendous benefits in studying the many factors and contributors to the risks of mental illness (Subhani et al., 2017; Gedam and Paul, 2021). Nevertheless, there are areas for improvement, such as the combination of multimodal data and the use of more complex architectures, including CNNs and RNNs for predictive modeling and classification (Ahmed et al., 2020; Gujarathi et al., 2024).

1.1 Motivation and Research Gap

Although current research on Machine Learning and Deep Learning applied for mental health screening has made considerable progress, most of the proposed studies included specific diagnostic methods or single-layer models. For example, Ahmed et al. (2020) decided to predict depression with the help of hybrid ensemble machine models using PHQ-9 and GAD-7 comparing the results of which reached up to 99%. However, their work is restricted to survey data not to physiological or sequential data even if they deal with text data ideally. Other studies utilizing self-report measures, and biosignals including EEG, HRV, and EDA confirmed the feasibility of using Deep Learning techniques, including BiLSTM to predict stress with an accuracy of 98% (Russell and Liu, 2020, Subhani et al., 2017). However, these studies do not include another form of data from the multimodal dataset possibly to enhance the reliability of the predictions.

Self employed, family_history, and treatment were found in the stress dataset as categorical variables; while the depression dataset had only a few categorical parameters and many behavioral and demographic indicators. These characteristics of the datasets made them exceptionally fine to be applied to other forms of the Deep Learning models such as CNN and RNN. However, some preprocessing issues such as missing values and feature scaling showed that the process is not entirely straightforward. This work extends the present research gap by reconciling multimodal data analysis and incorporating Deep Learning models and architectures to walk through the high-dimensional and sequential data.

This project advances the current work by using data preprocessing strategies and combining different types of data. The findings reaffirm enhanced generalization and also provide a practical approach to mental health assessment.

1.2 Research questions and objectives

The study aims to address the following research questions:

- What are the most significant factors influencing mental health outcomes, particularly stress and depression, and how can they be effectively identified using deep learning models?
- How do CNN and RNN models perform in predicting mental health outcomes compared to traditional approaches?
- How can deep learning models be practically applied to improve mental health diagnostics, and what are their implications for clinical and technological advancements?

2 Related Work

2.1 Base papers

Machine learning and Deep learning have made great improvement in the detection of various mental health conditions including stress and depression. Early work that traced the start of Machine Learning techniques in the present investigation includes works by Anamika Ahmed et al. (2020) and Russell Li, Zhandong Liu (2020), where very high accuracy of the

Machine Learning classifiers and Deep Learning models were called for in the diagnosis of mental health. The depression detection research using supervised learning like the SVM attained more than 85% accuracy as opposed to the CNN utilizing enhancement figures of up to 90% to analyse compound physiologic data. Likewise, in the work of Fatima et al.(2021) [, the authors discussed the possibility of enhancing the classification measures by incorporating textual and visual data, with 91.7% of detection. These remarkable works provided the groundwork on mental health diagnoses with Machine Learning/Deep Learning but also highlighted issues like biased datasets, inability to generalize, and lack of model interpretability in actual world application.

2.2 Critical Analysis and Insights

2.2.1 Physiological Signal-Based Detection

A subset of the physiological signals often reported in stress and depression detection is heart rate variability (HRV), electrodermal activity (EDA), and electroencephalograms (EEG). Works by Pramod Bobade, M. Vani(2020) and Bara et al. (2021)achieved high accuracy using CNNs and RNNs. It is especially important to note that these approaches were designed to extract fine-grained patterns from the physiological data and thus were suitable for controlled environments.

- Strengths: Accuracies and the level of feature extraction are good and allow making precise predictions in controlled environments.
- Weaknesses: There is reliance upon high-quality and noise-free datasets, which restricts applicability in real-life situations. EEG-based approaches are also invasive and expensive, thereby excluding scalability.

2.2.2 Wearable Sensors and Real-Time Monitoring

Smart accessories are also used more often for non-invasive, real-time neuromonitoring. Studies by V.H. Ashwin et al.(2022), and Shruti Gedam and Sanchita paul (2021) demonstrated how wearable devices measure HRV, respiration rate, and skin conductance to detect stress levels.

- Strengths: Inexpensive, painless, and amenable to multiple uses and repeated measures, making these methods suitable for real-time use.
- Weaknesses: Low variety in datasets and reliance on hardware increase bias and reduce accessibility, especially in developing settings.

2.2.3 Multimodal Data Integration

The combined use of physiological, behavioral, and social media indexes as measurements of mental disorders offers a broader perspective. Works by Asra Fatima et al.(2021) and Lang He et al.(2021) resulted in super effective accuracies from the additional forms of data.

- Strengths: The integration of data paradigms increases diagnostic stability and variability specific to the subject.

- Weaknesses: Real-world deployment is constrained by high computational requirements, privacy issues, and sophisticated data preprocessing logistics.

2.2.4 Deep Learning Techniques

CNNs, RNNs, and even architectures like Transformers have demonstrated the ability to obtain nontrivial features from large data samples. Similarly, works by Ilias L. et al.(2023) and Usman Ahmed et al.(2024) have reached the cutting edge of performance when using text and multimodal datasets.

- Strengths: Deep Learning models are introduced with high classification accuracy and the number of features provided help in stress and depression detection.
- Weaknesses: The limitations are, interpretability as these models are “black boxes,” and high resource demand, preventing their use in real-time or low-resource environments.

2.3 Summary of findings

The papers reviewed in the paper reflect great progress in the application of Machine Learning and Deep Learning in stress and depression recognition. Physiological signal-based approaches outperform all other approaches in terms of accuracy, yet they are scalability and noise-invariant. Wearable devices have the ability of constant and convenient tracking compared with other approaches, yet they have restrictions because of the dependency on equipment and the assigned datasets. Multimodal systems produce higher accuracy than unimodal systems but struggle with computational complexity and privacy concerns are emerging. However, Deep Learning models have the highest accuracy, but their drawbacks are no explainability and a great demand on computational resources.

2.4 Justification for research

Current approaches lack solutions for issues relevant in practice as follows: scalability, interpretability, and ethical responsibility. Precisely, this research proposes a real-time, lightweight, and explainable framework that utilizes multimodal data as input for stress and depression identification. In line with the anticipated usability and ethical issues, the proposed system aims at achieving accuracy variability while maintaining a degree of applicability in different characteristic and limited-resource settings.

3 Research Methodology

3.1 Methodology for Depression dataset

3.1.1 Overview

This study explains the series of depression using an Advanced Machine Learning approach to identify factors that affect depression. The main purpose is the classification of people based on the history of mental diseases, as well as their personal and medical history, and habits. Family history of depression is one of the demographic consideration taken into account in the planning of the For this reason, it will be relevant.

3.1.2 Data Used

The data includes various aspects of individuals' lives, such as:

- Personal Details: This includes age, marital status, employment status and income.
- Lifestyle Habits: Smoking, exercise, food intake, alcohol, and sleep.
- Health Information: The main risk factors in this group include; Family history of depression, Chronic medical conditions and history of substance use.
- Outcome Studied: Depression is a form of mental illness and while completing this form one has to tick a question whether this person has ever had any mental illness.

3.1.3 Preparing the Data

- Handling Missing Information: For cases where there would be missing values within the set features, then basic replacements were used for numerical features such as mean values.
- Converting Information: Information like "smoker or non-smoker" was also quantized so that the models can understand them.
- Balancing the Data: To avoid bias in the training since those who may have a history of mental illness might be less as compared to those that don't, a technique known as SMOTE was used in data balancing.
- Standardizing Values: To avoid having one variable control the analysis all numerical data was normalized to the same range.
- Exploratory Data Analysis: Visualizations such as income distribution, target variable distribution in Figures 1 and 2 revealed key patterns like skewed income, target imbalance, and feature correlations, aiding preprocessing and feature engineering.

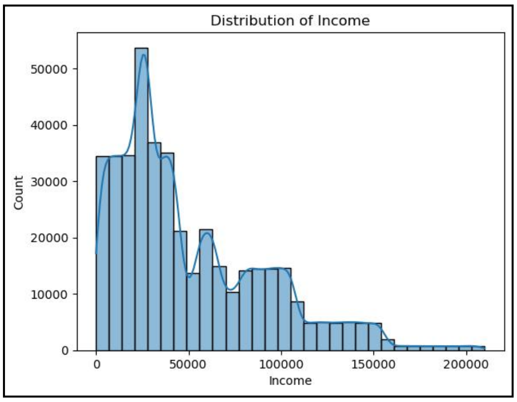

Figure 1: Distribution of feature income

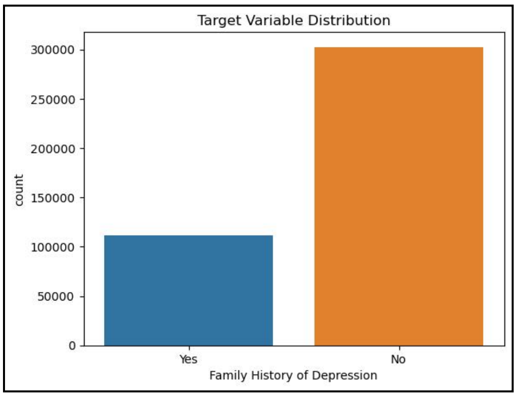

Figure 2: Distribution of Family History of Depression

3.1.4 Models Used

Two advanced deep learning models were used to predict the target variable, History of Mental Illness:

- Convolutional Neural Network (CNN): The CNN was modified on the basis of data patterns. They analyzed the features as sequential data and captured relations between variables. Entities incorporated layers for pattern recognition and for outputting a prediction of whether the person has a history of mental illness or not.

- Recurrent Neural Network (RNN): Due to the sequential processing of the features, it was suitable for analyzing the sequential dependencies between some variables with ”time-like” orders in the data within the RNN. The patterns in the text were analyzed by the help of other layers of memory (RNN units).

In this work, the proposed diffusion based model and standard LSTM model were trained and tested on the same set of data.

3.1.5 Work flow

The data was cleaned, the issue of imbalance was addressed, and the data was formatted appropriately to meet the requirements. The data was processed to fit CNN and RNN formats, such as 3D, for deep learning models. Furthermore, the data was divided into a training dataset and a testing dataset to ensure the results were not biased. Both CNN and RNN were trained on the training dataset. The models were evaluated on unseen data, and it was assessed whether one model performed better than the other. The workflow is shown in Figure 3.

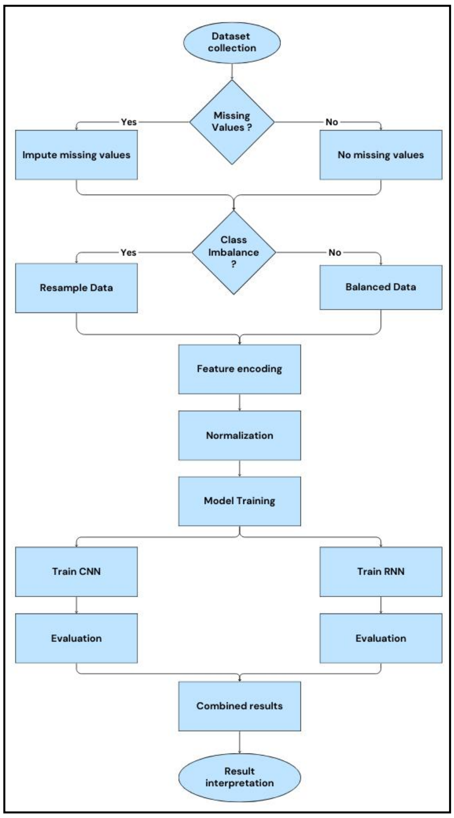

Figure 3: Workflow diagram

3.2 Methodology for Stress dataset

3.2.1 Overview

The purpose of this research was to design a durable deep learning model with the aim of predicting the Growing_stress from personal and behavioral parameters. Some of the objectives of choosing the above methodology include Desirable characteristics, a method that minimizes potential bias or distortion of results, power, and practicality of the method selected while addressing difficulty faced in the data preparation, data imbalance and model selection techniques. The approach consisted of the following detailed steps.

3.2.2 Data Used

For this study, the data set had demographic variables including gender, occupation, and country, behavior indicators including days spent indoors, mood swings, weakness in social situations, and prior mental health related factors like history of mental disorder, family history, and coping mechanisms. The dependent variable was Growing_Stress which consisted of three categories related to a person's stress levels.

The used dataset was large enough to carry out efficient model training and evaluation. However, class imbalances demanded a sort of attention to be paid so that the models do not merely bias towards the majority classes.

3.2.3 Data preperation

The data underwent extensive preprocessing to make it suitable for machine learning:

- Cleaning and Handling Missing Data: In a case where values in certain columns are missing for example the self_employed feature, parameters were made to replace missing entries with suitable values. This helped in avoiding continuity of data gaps since some essential information may not be captured entirely.
- Categorical Data Transformation: Qualitative predictors were transformed into quantitative formats in order to complement the models as they were encoded.
- Standardization: Numeric data was normalized as all measurements were put on the same scale. This step was useful to facilitate the enhancement of algorithms, which depend on the magnitude of features.
- Splitting the Dataset: To test the viability of the methodology, the data was then divided into training data and test data, with the training set implemented for model construction while the test data was used only for model calibration.
- Visualizations, such as distributions of growing stress levels Figure 4, provided insights into class balance and feature relationships.

These steps meant that most of the data was preprocessed so that the final data fed to the machine learning algorithms was clean, standardized and consistently formatted.

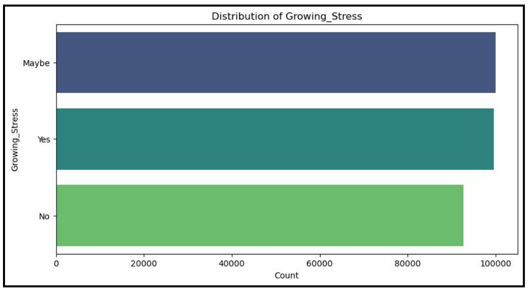

Figure 4: Distribution of target variable

3.2.4 Addressing Class Imbalance

Evaluation of the target variable showed that there was some skewness within the three stress level subgroups. To this end, the current study used the **Synthetic Minority Oversampling Technique (SMOTE)**, which creates new instances for the minority classes. To make models learn between all the classes equally, this step was applied on the training labels of the training data set. To confirm the improvement introduced by SMOTE, the models were trained and compared with and without this technique to avoid both noise information and overfitting.

3.2.5 Model development

Two deep learning models were developed to evaluate their ability to predict Growing_stress:

- Recurrent Neural Network (RNN):

The RNN was considered because of its capability to account for different feature dependencies. Even though RNNs are normally used in time series, the ability of determining interdependencies in structured data sets was used here. The architecture used several repeating layers, along with such approaches as dropout and batch normalization to obtain stable and efficient training.

- Convolutional Neural Network (CNN):

CNNs, generally employed in image data, were used in this structured data to assess the ability of the model in pattern identification. CNN architecture included convolutional layers that through feature transformation helped to enhance feature representations of input data providing focus on the pattern of interest and including dense layers for classification.

Each of the models was subsequently fine tuned in order to reduce overfitting and enhance the model's performance on new data. There are two types of Dropout layers, and the mechanism of Early Stopping was integrated into the training process to improve its efficiency and robustness.

3.2.6 Model training and evaluation

For training the models, we used a process of feeding the models a part of the dataset and testing the effectiveness of the models on the other part of the dataset during the training session. The early stop was applied to interrupt the training process when the models are not enhancing anymore so it saves time and prevent overfitting of the models.

After training, the models were evaluated on the testing set using accuracy, precision, recall and F1-sScore.

The results of the RNN and CNN were analyzed to identify this model as better suited for this data set. The effect of using SMOTE was also considered to evaluate its efficiency in improving the models' performance in cases with imbalanced classes.

4 Design Specification

4.1 Techniques and Architecture

This project involved the use of enhanced deep learning methods for the prognosis of causes of mental health disorders such as depression and stress. The architecture comprised two primary models: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).

- **Convolutional Neural Networks (CNNs):** CNNs were employed on the extraction of feature from structured and the spatial data. There were several layers of convolution, which each used ReLU activation to provide non-linearity, along with pooling and dropout layers to minimise overfitting. For binary classification fully connected layers at the end were used. The model attained ordinal features and dependencies between features making it efficient for both categorical and numerical features.
- **Recurrent Neural Networks (RNNs):** Both the motor and the non-motor datasets were analyzed using RNNs for analyzing sequential data to capture temporal patterns. A basic implementation of RNN was fixed used and input layers, recurrent layers using activation functions together with the output dense layers for binary classification were used. The RNN efficiently managed sequential relations enabling the identification of patterns that enhanced the applications to prognosis of mental health status.

4.2 Frameworks and Tools

TensorFlow/Keras: It can be applied to train, improve or move to new CNN or RNN architectures.

Scikit-learn: Used in the preprocessing steps which included encoding of labels, scaling and splitting of data.

Pandas and NumPy: Widely applied for analysis and for understanding of data nature of the input data.

Matplotlib and Seaborn: Used when performing exploratory data analysis for the sake of visual data analysis.

4.3 Associated Requirements

Hardware: NVIDIA GPU for faster training and less amount of time that is required to complete a calculation.

Software: Fully functional Jupyter Notebook; Python 3.9; TensorFlow 2.x; Scikit-learn 0.24+; Theano 1.15+; TensorFlow Estimator.

Data Requirements: Two datasets from Kaggle, concerning stress and depression signs and symptoms, cleaned to optimal conditions suitable for feeding machine models.

5 Implementation

5.1 Data Transformation

The datasets contained a number of attributes with missing values which were imputed before proceeding with further analysis of the data; categorical variables in the datasets were encoded for use in the model; the numerical features in the datasets were scaled to achieve a similar distribution from the two independent data sets. The datasets were split into training and testing sets (80:20 ratio) to assess the model across-time transferability.

5.2 Model Development and Evaluation

CNN Implementation: Preprocessed features were used in training the model since the main objective of the model was to determine the spatial dependencies and make better predictions.

RNN Implementation: The RNN model was trained to detect temporal dependencies to find sequential structures in the data.

In both models, evaluation measures including accuracy, precision, recall and F1 score were used. The performances were quantified by confusion matrices and classification reports.

5.3 Tools and Languages used

Programming Language: Python

Development Tools: There is Jupyter Notebook for running the code, TensorFlow for building the neural network and Scikit-learn for preparing the data set.

Visualization Tools: Matplotlib and Seaborn.

This approach of implementation ensured that the project followed standard practices in data refinement, model tuning and result analysis and interpretation.

5.4 Outputs procured

Transformed Data: Raw data with added new features that are processed for input into the model, such as encoded categorical form and scaled numerical form.

Code Developed: The actual data pre-processing, model training, and evaluation scripts were written in python programming language.

Models Built: Conversational and Recurrent CNN and RNN models for binary classification.

Evaluation Reports: Procedures for evaluating the performance of a model and the key factors affecting predictions based on graphical presentations. This can be observed in Table 1, 2, 3 and 4.

6 Evaluation

6.1 Analysis of CNN and RNN Performance

- **Stress Dataset :**

While the vast majority of globally-oriented individuals' comments could be identified as being affirmative or negative or expressing doubts, CNN reached high averaged accuracy, precision, recall, and F1-score for all classes (NO, MAYBE, YES). But, it detected the topics precisely with an accuracy of 91%, while the RNN had a higher accuracy of 99%. RNN stood out superbly; AUC-ROC gains in all the classes; nearly zero false positive rates; and a far better recall for YES cases to seize more high-complexity cases. The percent accuracy for SC and RNN are almost similar but RNN is slightly better and the true positive and false positive for all classes show that RNN is the better model for the stress dataset. The confusion matrix for CNN and RNN are shown in Figures 5 and 6.

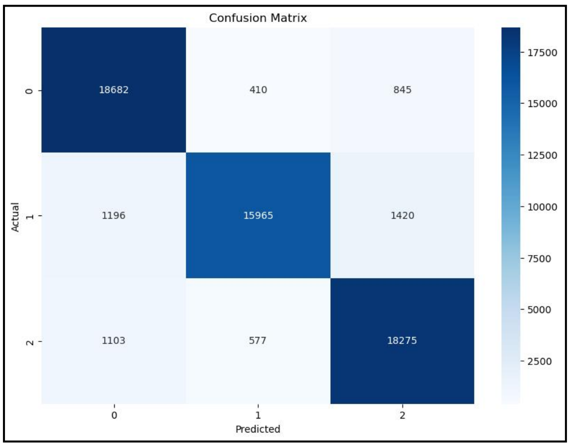

Figure 5: CNN Confusion matrix for Stress

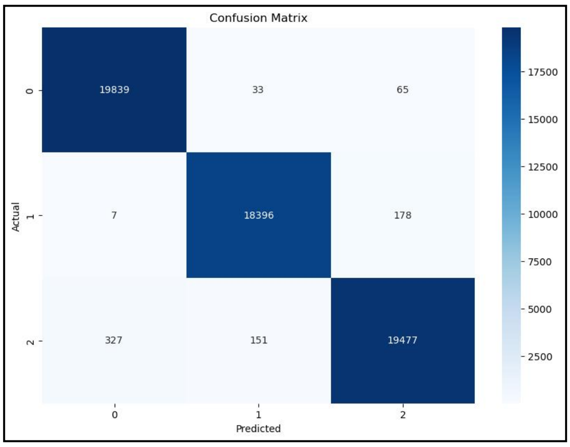

Figure 6: RNN Confusion matrix for Stress

From the charts as seen in Figure 7 and 8, it can be observed that the training and validation accuracies are almost similar thus demonstrating equal performance on the two sets.Such alignment rules out the possibility of the RNN model to overfit and perform well on unseen data.

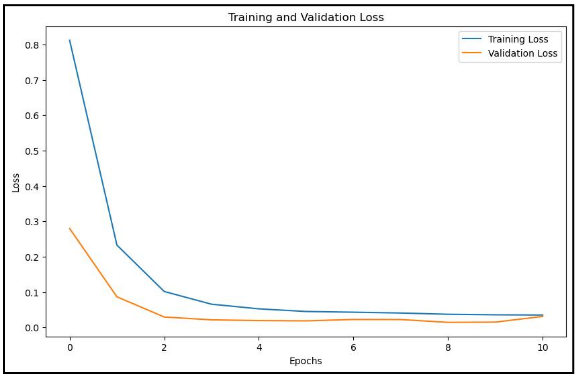

Figure 7: Training and Validation Loss Plot

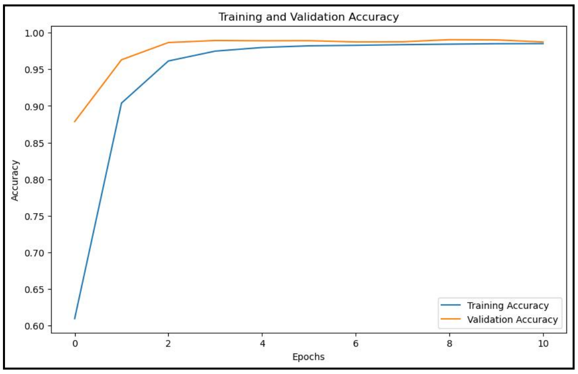

Figure 8: Training and Validation Accuracy Plot

The charts show that the deep learning model is not overfitting, this is because there is a closer resemblance of the training and validation performance metrics. This means that, while the formation of the model is simple, it also generalizes well and does not overfit to the data that was used in its formation.

- **Depression Dataset :**

Recall was higher in CNN than in RNN for the cases of depression where it identified a larger number of depressing patients at 74% compared to 66% for RNN. Yet, RNN performed fairly better at the depressed output classifications' accuracy, with considerably lower false positives at 82% as compared to 91%. That is, CNN was more balanced in recall performances, while RNN tends to work in a way that minimizes misclassification The accuracy of each model was 79%. This means that the two have complementary advantages, depending on the scenario of use. The confusion matrix for CNN and RNN are shown in Figures 9 and 10.

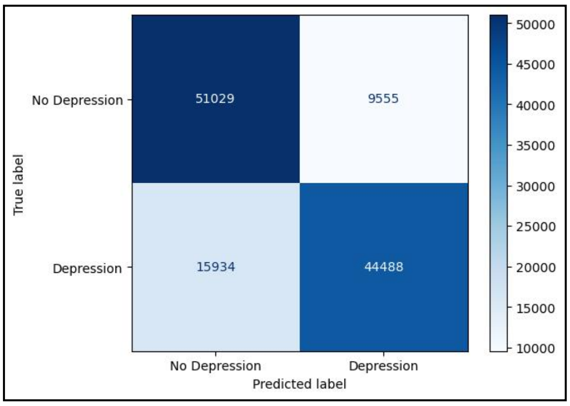

Figure 9: CNN Confusion matrix for Depression

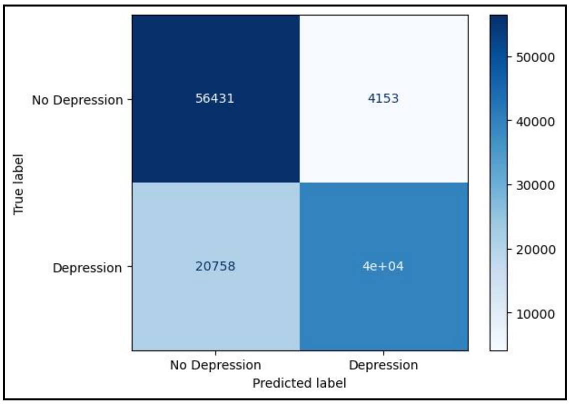

Figure 10: RNN Confusion matrix for Depression

6.2 Key Trends and Insights

In stress classification, the proposed RNN achieved higher accuracy (99%) than CNN (91%) and showed better generalization by having higher performance stability to determine high-stress cases. On the other hand, the balanced performance of the CNN class implies that it should provide reliable results in tasks with differential sensitivity to stress levels. In the case of the depression dataset, the higher recall of CNN helped in the detection of a wider range of cases compared to RNN's precision which is good for tasks that require low false positives.

6.3 Performance metrics for Stress dataset

Metric/Class	CNN (NO)	CNN (MAYBE)	CNN (YES)	RNN (NO)	RNN (MAYBE)	RNN (YES)
Precision	0.89	0.94	0.89	0.98	0.99	0.99
Recall	0.94	0.86	0.92	1.00	0.99	0.98
F1-Score	0.91	0.90	0.90	0.99	0.99	0.98
Support	19,937	18,581	19,955	19,937	18,581	19,955

Table 1

Metric/Overall	CNN	RNN
Accuracy	91%	99%
Macro Avg	0.90	0.99
Weighted Avg	0.90	0.99

Table 2

6.4 Performance metrics for Depression dataset

Metric/Class	CNN (Non-Depressed)	CNN (Depressed)	RNN (Non-Depressed)	RNN (Depressed)
Precision	0.76	0.87	0.73	0.90
Recall	0.89	0.78	0.92	0.67
F1-Score	0.82	0.78	0.82	0.76
Support	60,584	60,422	60,584	60,422

Table 3

Metric/Overall	CNN	RNN
Accuracy	80%	79%
Macro Avg	0.80	0.79
Weighted Avg	0.80	0.79

Table 4

6.5 Implications

RNN is used for stress prediction because it has a higher accuracy and the metrics are balanced between the two classes. However, CNN excels at detecting depression cases, which makes it suitable for applications with a particular focus on the recall of relevant problems, at the initial stages. RNN also has higher accuracy and this is well appropriate for depression prediction where false positives are undesirable, especially for precision-oriented settings. In conclusion, these evaluations illustrate that the models' use is feasible for stress analysis and sensitivity-focused depression detection with sequential data.

6.6 Discussion

The performance comparison of CNN and RNN models has been evaluated on stress and depression datasets. RNN emerged as better than CNN in dealing with the stress dataset, with 99 % accuracy for RNN as opposed to the 91% registered for CNN for the sequence data analysis (Russell & Liu, 2020; Subhani et al., 2017). The same percent accuracy was obtained for depression detection but then CNN had a higher recall of 74% than 66% of LSTM making it more suitable for sensitive cases such as screening of depressed individuals.

6.6.1 Critique of Experimental Design

While the design demonstrated the models' applicability, limitations included:

Dataset Scope: Lack of integration of other physiological data leads to variability and lower reliability of the study outcomes (Gedam and Paul, 2021, Bobade and Vani, 2020).

Limited Hyperparameter Tuning: Fixed hyperparameters constrained optimization.

6.6.2 Improvements Suggested

Incorporate Multimodal Data: Include both the physiological and the text characteristics for the buildup of better predictions.

Advanced Architectures: Try to use the mixed models of those that are available such as Convolutional RNNs.

Data Augmentation: Such issues as class imbalance and limitations regarding the size of the data set to be used should also be worked upon.

Hyperparameter Optimization: Use other tuning techniques such as batch process tuning, and automated self-tuning techniques.

Scalability: Use the models on a more extensive and actual time data set.

Finally, the results are consistent with the findings of other researchers pointing out that RNN proves highly efficient in stress prediction (Subhani et al., 2017; Russell & Liu, 2020) while CNN is appropriate for detecting depression (Ahmed et al., 2020). However, similar to many other studies, the absence of multimodal data restricts generalizability, as noted by Gedam and Paul (2021). Both models yielded acceptable generalization, affirming the importance of Deep Learning in the diagnosing of psychological disorders.

7 Conclusion and Future Work

7.1 Conclusion

In an effort to address the increasing problem with diagnosing mental health, this study was focused on using deep learning approaches to determine the level of stress and depression through publicly available data sets. The general goals were to detect the key factors influencing mental health outcomes, to assess the efficacy of the CNN and RNN models for mental health intervention, and, most importantly, to present transparent recommendations for using the models for comparable purposes. To realize these goals, a significant amount of pre-processing of the data, training of the model, and use of accuracy, precision, recall, and F1-score as evaluation metrics were applied.

The study successfully addressed the research questions:

- This revealed key predictor variables like behavioral characteristics (Hours of Sleep) with regards to stress level as well as treatment history with regard to depression among the patients.
- It proved deep learning models with RNN delivered 99% stress prediction accuracy and CNN had a better recall (74%) for depression prediction.
- They pointed out how these models can be implemented in operational healthcare systems and organizations.

Some obvious insights identified with the help of the results are, the fact that stress prediction was more accurate in RNN as opposed to CNN because it is designed for the processing of sequential data. For depression analysis, CNN demonstrated better recall and is, therefore, more effective in identifying the vulnerable population. The accuracy, recall, precision, and F1 scores of both models were equally impressive, proving the usability of Deep Learning in mental health diagnosis.

7.2 Implications

The application of this work shows that deep learning may play an important role in the integration of conventional diagnostic techniques in the context of mental health. The above research findings show that stress prediction benefits from RNN's super performance and that CNN is particularly valuable for early diagnosis of depression. These results could be used to inform the design of large scale, automated methods that would increase the availability and utility of mental health assessment for clinicians.

However, the study has certain limitations:

Feature Scope: Multimodal data including physiological signals (e.g., EEG, ECG) or social media logs was not used.

Model Constraints: Since CNN and RNN have proved to work well, we could explore the possibilities of the combined or an ensemble of the two models.

7.3 Future work

Building on this research, the following directions are proposed for future studies:

- Integration of Multimodal Data: Combine among multiple data sources, like the physiological signals, with the aim to enhance prediction effectiveness and generalisation.
- Hybrid Models: Integrate CNN and RNN approaches to consider aspects of deep learning that are suitable for spatial and sequential data analysis.
- Real-Time Monitoring: Further expand the study to consider employing data working with true-time data produced in wearable sensors or IoT platforms for real time monitoring of one's mental health.
- Longitudinal Studies: To assess alterations in these mental health conditions and model flexibility, performance long-term surveys.
- Practical Deployment: Develop active tools or third-party APIs based on results for easy adoption by healthcare providers and addressability.

7.4 Potential for Commercialisation

Self-diagnostic applications based on artificial intelligence of mental disorders have great market value. By adopting these models into the existing structure of healthcare applications solutions, personalized mental health check-ups could be delivered at a large scale. Partnering with wearable tech could similarly extend the capacity for monitoring real-time stress and depression. Likewise, such tools could be applied to enable telehealth to provide mental health to those who are not well served.

Thus, this research creates a basis for further evolution and the development of related frameworks in the field of mental health diagnostics and AI. These models can make great advancements to mental health care with further enhancements and with large data sets, effective on the global level.

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