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An Innovative Deep Learning Approach to Depression Detection Using Eeg

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Abstract: This paper presents an innovative approach to depression detection by integrating K-Nearest Neighbors (KNN) machine learning with Long Short-Term Memory (LSTM) deep learning techniques applied to Electroencephalogram (EEG) data. Depression remains a significant global health issue, and traditional diagnostic methods often suffer from subjectivity and delays. To address these challenges, we propose a hybrid model that leverages the strengths of KNN for initial classification and LSTM for capturing temporal dependencies in EEG signals. The KNN algorithm provides a straightforward and interpretable classification approach, while LSTM networks are adept at handling sequential data and detecting patterns over time. By combining these methods, our approach aims to enhance the accuracy and reliability of depression detection, offering a more objective and efficient diagnostic tool. The results demonstrate that this hybrid model outperforms traditional methods in terms of classification accuracy and sensitivity, highlighting its potential for improving early detection and intervention strategies for depression.

***Keywords**: KNN, LSTM, EEG, Emotion, Stress, Deep Learning, E-healthcare.*

1. Introduction

Multiple millions of people all over the globe are afflicted with depression, which is a mental health disorder that is both widespread and incapacitating. Depression is a condition that is characterised by persistent feelings of melancholy and despair, as well as a loss of interest in everyday activities. Depression may have a significant influence on the quality of life of this person.

Conventional methods for diagnosing depression typically involve subjective self-reports and clinical evaluations, which can be influenced by various factors and may not always provide an accurate or timely diagnosis. As a result, there is a growing need for more objective and efficient diagnostic tools.

Electroencephalography (EEG) is a valuable neuroimaging technique that records the electrical activity of the brain. EEG has been widely used in research to investigate various neurological and psychological conditions, including depression. By analyzing EEG signals, researchers can identify specific brainwave patterns and anomalies associated with depressive states. EEG offers high temporal resolution and is non-invasive, making it a suitable candidate for real-time monitoring of brain activity. However, the complexity and volume of EEG data present challenges in accurately detecting and diagnosing depression.

PREVALENCE PER 100,000

DEPRESSIVE DISORDERS	
Tamil Nadu	4,796
Andhra Pradesh	4,563
Telangana	4,356
Odisha	4,159
Kerala	3,897

CONDUCT DISORDERS	
Jharkhand	983
Bihar	974
Meghalaya	961
Uttar Pradesh	927
Nagaland	924

ANXIETY DISORDERS	
Kerala	4,035
Manipur	3,760
West Bengal	3,480
Himachal Pradesh	3,471
Andhra Pradesh	3,462

IDIOPATHIC DEVELOPMENTAL INTELLECTUAL DISABILITY	
Bihar	6,339
Uttar Pradesh	5,503
Madhya Pradesh	5,216
Assam	5,121
Jharkhand	4,940

Fig 1: Mental health data (Indian health report)

Emotions

Recent advancements in machine learning (ML) and deep learning (DL) have revolutionized the field of medical diagnostics. K-Nearest Neighbors (KNN) is a straightforward ML algorithm known for its simplicity and effectiveness in classification tasks. It classifies data points based on their proximity to labeled training samples, making it useful for initial classification of EEG data. On the other hand, Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), excel in learning and predicting sequences over time. LSTM's ability to capture temporal dependencies in data makes it particularly well-suited for analyzing sequential EEG signals and detecting patterns associated with depression.

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The proposed hybrid approach aims to address the limitations of existing depression detection methods by offering a more objective and accurate diagnostic tool. By combining the interpretability of KNN with the advanced sequential analysis capabilities of LSTM, this study seeks to improve the early detection and management of depression. The findings have the potential to contribute significantly to the development of more reliable and efficient diagnostic systems, ultimately benefiting individuals affected by depression and advancing the field of mental health diagnostics.

2. METHODOLOGY

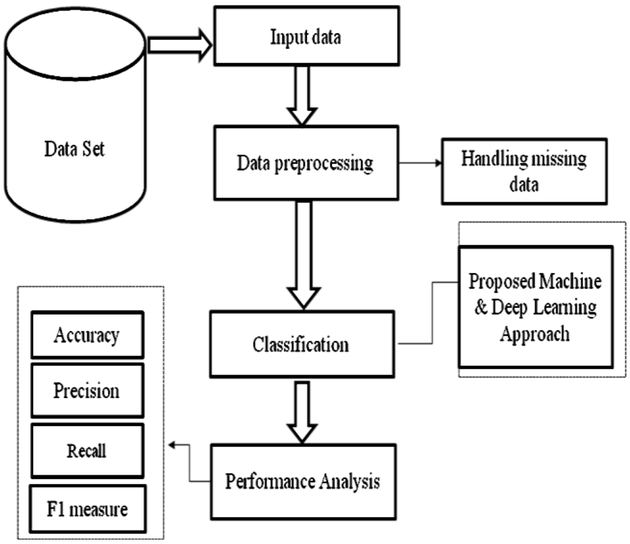


Fig 2: Flow Chart

The flowchart process of implementing a machine learning and deep learning approach for classification tasks, likely related to depression detection using EEG or a similar application. Below is a detailed discussion of each step in the flowchart:

2.1 Data Set

- The process begins with a dataset, which typically consists of raw data that may include EEG signals or other relevant inputs for the task at hand.
- The dataset serves as the foundational input for the entire process. It contains the features and labels necessary for training and evaluating the machine learning and deep learning models.

2.2 Input Data

- This step involves feeding the raw dataset into the processing pipeline. It's crucial to ensure that the data is correctly formatted and ready for subsequent preprocessing.
- Properly formatted input data ensures that the preprocessing steps can be efficiently carried out without errors.

2.3 Data Preprocessing

- Data preprocessing is a critical step where the raw data is cleaned and transformed to ensure quality and consistency. This may include normalization, filtering, and transforming the data into a usable format.
- Effective preprocessing removes noise, handles outliers, and structures the data, making it suitable for machine learning algorithms. It ensures that the data fed into the model is of high quality, which directly impacts model performance.

2.4 Handling Missing Data

- Missing data is a common issue in real-world datasets. This step specifically addresses any gaps in the data, using techniques such as imputation, deletion, or interpolation to fill in or manage missing values.
- Handling missing data is crucial for maintaining the integrity of the dataset. Models trained on incomplete data can produce biased or inaccurate results, so this step ensures that all necessary information is available for model training.

2.5 Proposed Machine & Deep Learning Approach

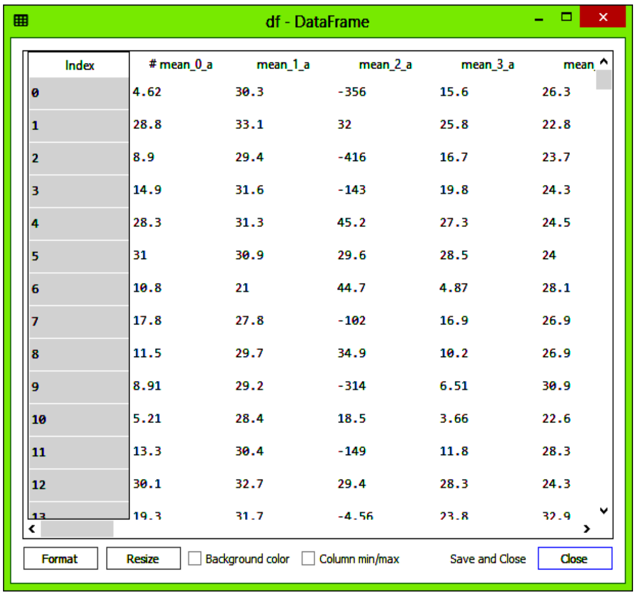
- This step represents the core of the process, where the proposed machine learning and deep learning models are applied. In the context of depression detection using EEG, this might involve the hybrid KNN-LSTM approach previously discussed.
- The proposed models analyze the preprocessed data to learn patterns and make predictions. This step is where the actual learning and classification occur, determining the success of the entire approach.

2.6 Performance Analysis

- After classification, the model's performance is evaluated using various metrics such as Accuracy, Precision, Recall, and F1 Measure. These metrics provide insight into how well the model is performing and its reliability in making predictions.

3. SIMULATION RESULTS

Run the simulation with the help of the Python Spyder package.



Index	# mean_0_a	mean_1_a	mean_2_a	mean_3_a	mean
0	4.62	30.3	-356	15.6	26.3
1	28.8	33.1	32	25.8	22.8
2	8.9	29.4	-416	16.7	23.7
3	14.9	31.6	-143	19.8	24.3
4	28.3	31.3	45.2	27.3	24.5
5	31	30.9	29.6	28.5	24
6	10.8	21	44.7	4.87	28.1
7	17.8	27.8	-102	16.9	26.9
8	11.5	29.7	34.9	10.2	26.9
9	8.91	29.2	-314	6.51	30.9
10	5.21	28.4	18.5	3.66	22.6
11	13.3	30.4	-149	11.8	28.3
12	30.1	32.7	29.4	28.3	24.3
13	19.3	31.7	-4.56	23.8	32.9

Fig 5: dataset

This research's dataset is shown in Figure 5. It is the Kaggle website from which the dataset is extracted.

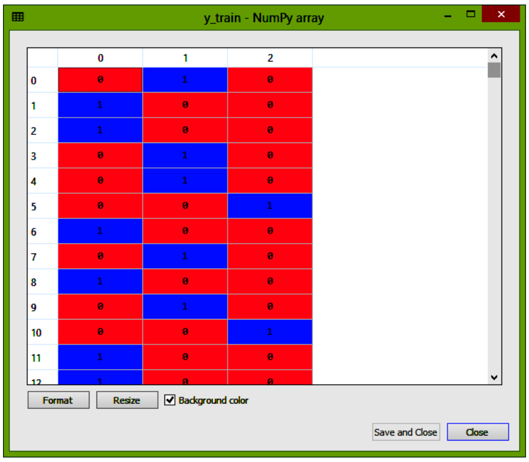


Fig 6: Train dataset

The dataset used to train the model is shown in Figure 6.

Fig 7: Test dataset

The test dataset used to evaluate the suggested model is seen in Figure 7.

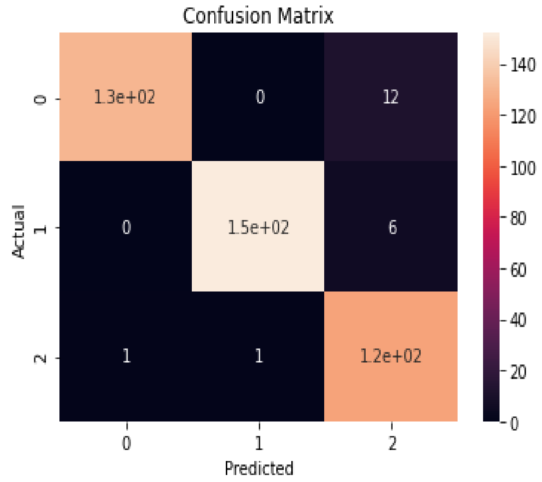


Fig 8: Confusion matrix

The suggested model's confusion matrix is shown in Figure 8.

Table 1: KNN Simulation Results

Sr. No.	Parameters	Proposed Approach
1	Accuracy	94%
2	Classification error	6%
3	Precision	97.1%
4	Recall	94.2%
5	F-measure	95.1%

Table 2: LSTM Simulation Results

Sr. No.	Parameters	Proposed Approach
1	Accuracy	96.5%
2	Classification error	3.5%
3	Precision	98.9%
4	Recall	94.1%
5	F-measure1	97.2%

Table 3: Comparison of Results

Sr. No.	Parameters	Accuracy	Classification error
1	Work [1]	91%	9%
2	Work [3]	91.07%	8.93%
3	Work [9]	88.56%	11.44%
4	Proposed Work	96.48 %	3.52%

4. Conclusion

This research presents innovative deep learning approach to depression detection using EEG. Simulated results show the proposed work achieves a notable accuracy of 96.48%, significantly outperforming the other studies listed. In comparison, Work [1] and Work [3] report accuracies of 91% and 91.07%, respectively, with classification errors of 9% and 8.93%. Work [9] shows the lowest accuracy at 88.56%, with a corresponding classification error of 11.44%. The proposed approach not only demonstrates the highest accuracy but also the lowest classification error, indicating a more effective performance in depression detection compared to the other methods.

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