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Comparative Performance Analysis of Deep Learning Models for EEG-Based Stress Detection Using Different Feature Extraction Methods

Goldy Saini[1], Rakesh Kumar[1], Lokesh Malviya[2],

[1]Department of Computer Science & Engineering, Rabindranath Tagore University, Raisen, Madhya Pradesh, India
[2]School of Computing Science and Engineering, Vit Bhopal University, Sehore, Madhya Pradesh, India

Abstract-This study emphasising dimensionality reduction techniques (PCA and FAST-ICA) and frequency bands (Alpha, Beta, and Theta), investigates the performance of three deep learning models—LSTM, GRU, and hybrid LSTM+GRU—in stress detection using EEG inputs. Evaluating and contrasting the models' performance for accuracy, precision, recall, and loss under several conditions was the primary goal. Using EEG data, the models were trained and assessed; the results show their ability to interpret sequential data and detect stress-related patterns. Using PCA and FAST-ICA, the study reduced dimensionality and preserved important features from the EEG signals, hence improving model efficiency. Over all frequency ranges and dimensionality reduction techniques, the results show that the GRU model often beats both LSTM and the Hybrid LSTM+GRU. With the lowest loss values and the best average accuracy—up to 99.45%—GRU showed remarkable resilience and optimisation. Particularly in precision and recall, the hybrid model showed strong performance; yet, for accuracy and loss reduction, it considerably underperformed relative to GRU. Though LSTM showed stability, usually it performed worse than the other models. The most successful model for stress detection proven to be the GRU model, which is adept in handling sequential data and reducing vanishing gradient problems.

Keywords- Stress Detection, EEG Signal, Dimensionality Reduction, PCA, Fast-ICA, and Deep Learning Models

I. INTRODUCTION

Affecting people's well-being, productivity, and general quality of life, stress is a crucial physiological and psychological disorder. Early detection and good stress management have become ever more vital given the fast speed of modern life. By means of pattern of brainwave activity analysis, electroencephalography (EEG) signals—which record electrical activity in the brain—offer a non-invasive and dependable means of stress detection[1]–[8]. Because EEG signals offer real-time data reflecting an individual's cognitive and emotional states, they are very good in stress detection. Deep learning models and enhanced feature extraction methods have greatly advanced the field of stress detection and shown great promise for raising the accuracy and efficiency of stress classification systems[9], [10]. Analysing sequential data like EEG signals benefits especially from deep learning models including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and hybrid architectures like LSTM-GRU since they can learn temporal correlations and complex patterns inherent in these signals. Fast Independent Component Analysis (FAST-ICA) & Principal Component Analysis (PCA) help much to reduce data dimensionality and preserve relevant information, hence increasing the performance of stress detection models[2], [11]–[17].

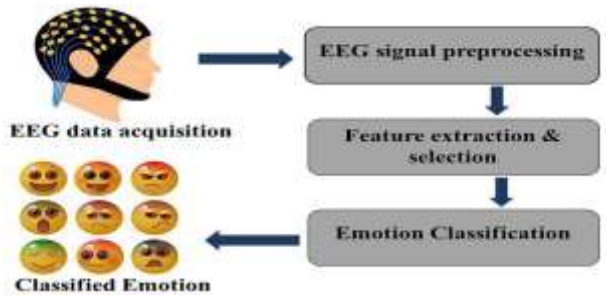


Figure 1 Stress Detection using EEG signal

This paper emphasises on the comparison of several deep learning models & feature extraction techniques evaluating their performance over important criteria including accuracy, precision, recall, and loss in order

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to identify the best effective way for stress detection using EEG data[18]–[24]. Stress appears in many frequency bands of EEG signals including Alpha, Beta, and Theta, each associated with various cognitive and emotional states. The Theta band is connected with emotional processing and mental exertion; the Alpha band is linked with relaxation and calmness; the Beta band reveals active thinking and worry. Understanding stress levels and their underlying brain processes depends on analysis of these frequency ranges. This paper investigates the performance of LSTM, GRU, and hybrid LSTM-GRU models using EEG data processed through PCA & FAST-ICA throughout these frequency ranges, so offering a thorough knowledge of how model architecture and feature extraction effect stress detection. The growing need for accurate and efficient stress detection systems that might be included into useful applications including wearable gadgets, mental health monitoring systems, as well as tools for occupational productivity drives this effort[25]–[27]. Conventional techniques of stress detection, including physiological measurements and self-reported questionnaires, are sometimes erroneous, time-consuming, and subjective. Using cutting-edge computing methods to give real-time insights into a person's stress levels, EEG-based stress detection presents an objective substitute. Adoption of deep learning models in EEG signal analysis has revolutionised the profession by allowing the automatic extraction of intricate patterns and therefore lessening of need on hand feature engineering. Still, choosing the best model and feature extraction method is difficult since the particular application and the features of the EEG data will affect the performance of these systems. This work attempts to close this disparity by methodically evaluating, on stress detection tasks, LSTM, GRU, and hybrid models incorporating PCA and FAST-ICA[28]–[33].

This work aims to find the best method for processing EEG signals and stress detection by comparing the models over several criteria. The results of this work should help to create strong and scalable stress detecting systems, therefore opening the path for their inclusion into useful applications. Moreover, the comparison of feature extracting methods emphasises the need of dimensionality reduction in improving model performance, therefore providing insightful information for field practitioners and researchers. Beyond stress detection, the relevance of this research goes beyond approaches and insights acquired from this study to other fields including emotional recognition, cognitive load assessment, and neurological illness diagnosis utilising EEG signal processing. This work is to progress the state-of-the-art in EEG-based stress detection by using the strengths of deep learning models and advanced feature extraction techniques, so laying a basis for future research and invention in this important field. In order to solve practical issues in mental health and well-being, our work emphasises finally the transforming power of merging EEG signal analysis with deep learning.

II. LITERATURE REVIEW

Stress affects not just physical condition but also one's performance in daily life, especially in the workplace. The link between psychological stress and its aetiology emphasises the need of early stress identification to stop the spread of disease and save life. Monitoring psychological signals often uses electroencephalography (EEG), which logs brain rhythms as electric waves. Recent studies, such those by Roy et al. (2023) [14], concentrate on efficiently detecting stress by processing multichannel EEG data utilising automatic feature extraction methods leveraging In this context, traditional deep learning models including CNN, LSTM, BiLSTM, GRU, and RNN have been routinely used; hybrid combinations show interesting performance in managing non-linear brain signals and long-term dependencies. Roy et al. outperformed other models in classification accuracy by suggesting a new integration of DWT-based CNN, BiLSTM, and two layers of GRU to improve feature extraction and classification of stress levels. In a related line, Adhikary et al. (2023) [17] investigated EEG signals to identify personal mood. They obtained a detection accuracy of 96.01% by using several neural network techniques, Savitzky-Golay filtering and Independent Component Analysis for data filtration, and Particularly with noisy and sparse datasets, Kimmatkar and Babu (2022) [34] examined the difficulties experienced by deep learning and SVM models in emotion recognition. With an accuracy rate more than 90%, their suggested "Min of mean"

approach for grouping emotions based on EEG data demonstrated better performance than current techniques. Using the Multichannel Wiener filter for artefact removal and a quadratic time-frequency distribution for signal representation, Dairi et al. (2022) [35] presented an unsupervised deep learning system for mental task detection using EEG signals. Their DBN-based Isolation Forest approach showed better categorisation than several EEG-based approaches. Ahmad et al. (2022) [36] examined the use of machine and deep learning models in the diagnosis of epileptic seizures, emphasising the difficulties presented by the low amplitude and non-stationarity of EEG. The review emphasises the need of choosing the appropriate feature extraction techniques and ML/DL models to increase diagnosis accuracy even if the development in EEG-based seizure diagnosis marks great progress. These investigations show enhanced performance in stress detection, mood analysis, emotion recognition, mental task classification, and seizure diagnosis, so highlighting the increasing promise of EEG-based deep learning models for many psychological and neurological use.

Table 1. Literature Summary

Author / Year	Author / Year	Method	Research Gap	Controversies	References
Omneya Attallah -2025	Omneya Attallah -2025	Machine Learning SVM, KNN,LDA	For large dataset Deep Learning Not used	Still Accuracies by LDA 90%	[41]
Sivasankaran Pichandi -2025	Sivasankaran Pichandi -2025	Hybrid optimization technique for feature extractionBiLSTM	Model Optimization not perfored	Zebra-chimp optimization (ZCO) fitness values achieved 96%	[42]
Shashibala Agarwal -2025	Shashibala Agarwal -2025	Young's Double Slit Experiment Optimizer (YDSE) , Short-Term Fourier Transform-Randon Transform (STFT-RT)	Current EEG ML techniques ignore repeated data, therefore influencing classification accuracy.	method achieved an accuracy of 97.8%	[43]
Hafeez, M.A-2024	LSTM and CNN	LSTM and CNN	Hybrid Models and Comparison Not Implemented	Still Accuracies are low 70 % For LSTM and 90% for CNN	[41]
Hun-gyeom Kim-2024	Five convolutional neural network (CNN) architectures and one Vision Transformer model	Five convolutional neural network (CNN) architectures and one Vision Transformer model	Hyperparameters and optimization not applied for models	ResNet-50, achieved the highest AUROC value of 95.40	[42]

Author / Year	Author / Year	Method	Research Gap	Controversies	References
Mathivanan/2023	Mathivanan/2023	DNN cleanliness and EEG representations help to detect driving tiredness.	Real-time EEG-based vehicle fatigue detection still presents difficult tasks for automation.	Still unresolved include high prices, accuracy trade-offs, or real-time EEG application difficulties.	[37]
Bashir/2023	Bashir/2023	Clinical diagnosis and MDD detecting accuracy are enhanced by EEG-based machine learning.	Restricted feature analysis reduces the diagnostic power of EEG-based MDD detection.	Feature selection dependability of EEG-based MDD diagnosis is under question.	[38]
Zhong/2023	Zhong/2023	KW test-based structure improves ML's detection of EEG disease.	Current EEG ML techniques ignore repeated data, therefore influencing classification accuracy.	More general validation is required for KW-based EEG illness detection reliability.	[39]
Mohan/2023	Mohan/2023	Deep CNN employing EEG signals precisely detects anxiety and despair.	Feature selection and limited EEG datasets impede more general depression-anxiety detection.	Features extraction techniques and little sample size could influence generalisation.	[40]
Kotte/2023	Kotte/2023	EEG emotion identification and categorisation accuracy is improved by fuzzy-based deep learning.	Restricted investigation of fuzzy-based deep learning methods for EEG emotion detection.	Issues regarding the complexity of pretreatment and constraints on classifier generalisation.	[12]

III. METHODOLOGY

In this Methodology using the DASPS dataset, the approach centres on EEG signal processing for stress identification. Focussing on Theta, Alpha, and Beta bands, data pre-processing consists in noise reduction with Butterworth filters and frequency band isolation utilising bandpass filters. PCA and Fast-ICA are used in feature extraction to lower dimensionality and emphasise pertinent stress trends. With PCA and Fast-ICA strengthening the feature sets, machine learning models—including LSTM, GRU, and hybrid LSTM-GRU—are used to categorise stress degrees. Trained

and evaluated on an 80-20 split of the data, the models maximise performance in stress detection using cutting-edge deep learning methods.

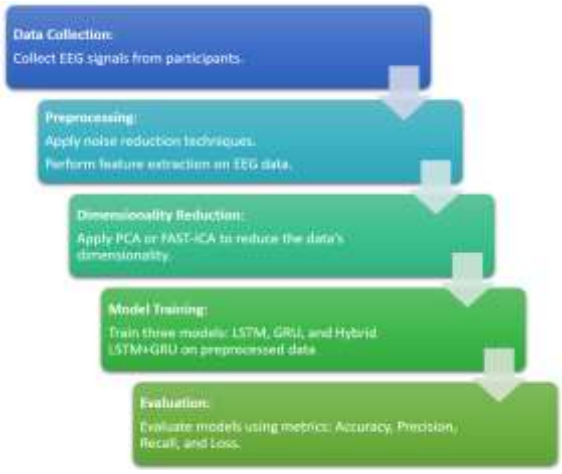


Figure 2 Proposed Flowchart

1. Data Collection

Accessible via IEEE Dataport, the DASPS Dataset is a freely available database intended for study on stress detection employing EEG signals. This dataset is a great tool for machine learning and deep learning research since it offers high-quality EEG recordings taken from subjects under situations that cause stress. Placed on the scalp according to the worldwide 10-20 system, it comprises impulses recorded from 14 electrodes—F3, F4, AF4, FC5, FC6, T7, T8, P7, P8, O1, and O2.

For every observation in the dataset, valence, arousal, and a labelled stress level (e.g., "High stress ") are also included, so supporting supervised learning applications. Numerical in nature, EEG signal values record brain electrical activity under several mental states. For example, signals in the above samples exhibit different patterns with high-magnitude values for particular electrodes including F3, F4, and FC5 in "High stress" situations.

With parameters like valence and arousal levels, this ordered dataset lets one thoroughly study brainwave patterns linked with stress. stress labels help stress detecting models to grow and be evaluated easier. By training deep learning models that estimate stress levels using this data, researchers can advance stress monitoring uses in healthcare and beyond.

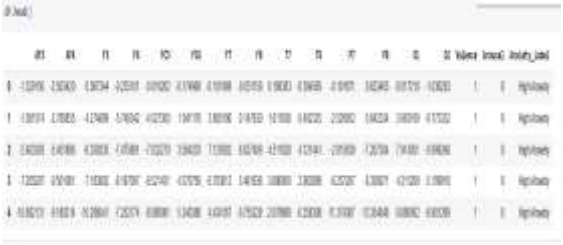


Figure 3 Data Frame

2. Data Pre-processing & Feature Extraction

Noise Filtering Using Butterworth Filter

Environmental interference, muscle movements, & equipment flaws are among the several external and internal causes of noise that can afflict EEG signals. This noise might compromise later analysis and modelling and masks the actual signal. The initial preprocessing step was a Butterworth low-pass filter used to help to offset this. Often renowned for its flat frequency response and ability to lower high-frequency noise without substantial signal distortion is the Butterworth filter. Since it ensures a flat response in the passband, it fits exactly for processing EEG signals.

Built using a Python code calculated depending on a given cutoff frequency, sampling rate, & filter order, the filter is Using the Nyquist frequency—half the sampling rate—the cutoff frequency was normalised, therefore guaranteeing accurate filtering. Running the filter on every EEG channel removed unwanted noise components, therefore keeping just the relevant low-frequency bits of the signal.

For channels F3, F4, T7, and T8, for instance, signals were separately processed and their filtered forms were maintained as additional columns in the dataset. This step not only improves the signal quality but also ensures the reliability of next feature extraction and categorisation. For exactly recognising stress trends, the free from high-frequency noise clean signals are more suited.

A Butterworth low-pass filtering with a transfer function defined helped with noise filtering:

$$H(s) = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_e}\right)^{2n}}} \qquad (1)$$

Where
- H(s): Gain of the filter
- ω: Signal frequency
- ω_e : Cutoff frequency
- n: Order of the filter

3. Band Selection Using Bandpass Filter

Next in preparation of EEG data is band selection—which isolates specific frequency bands matching to different brain activities. Among the several normal frequency bands separating EEG signals are theta (4–8 Hz), alpha (8–12 Hz), and beta (12–30 Hz). These ranges provide valuable fresh angles on mental states such stress, rest, or attention. Every channel got a bandpass filter to separate these specific frequency components, therefore ensuring the retention of merely relevant information.

created using a Python approach computing filter coefficients dependent on the necessary low and high cutoff frequencies, the bandpass filter was created against the Nyquist frequency. Separate datasets for the Theta, Alpha, and Beta bands were generated from the filter passing every EEG channel signal. To find their frequency-specific components, for instance, we filtered signals from channels including AF4, FC5, and FC6.

This technique allows one to investigate brain activity in numerous bands in very great detail. Specific bands—beta with high stress or alertness, theta with drowsiness, alpha with relaxation—link mental states for stress detection. Separating these bands helps the filtered data to be more significant, thus simplifying the signal and increasing the capacity of machine learning models to discover trends connected to stress.

Particular frequency ranges—such as Theta(4-8Hz), Alpha(8-12Hz), and Beta(12-30Hz)—were separated using bandpass filtering Mathematistically, the bandpass filter is expressed as:

$$H(\omega) = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_e}\right)^{2n}}} \; for \; \omega_{low} < \omega < \omega_{high} \quad (2)$$

Using Python, the filter coefficients were computed as:

$$b, a = butter(n, [\omega_{low}, \omega_{high}], btype = 'band' \quad (3)$$

The filtered signal for each frequency band was computed as:

$$\mathcal{Y}Band[n] = bandpass_filter(x_{Raw}[n], \omega_{low}, \omega_{high} \quad (4)$$

For example
- Theta Band (4–8 Hz):
- $\mathcal{Y}_{Theta}[n] = bandpass_filter(x[n], 4,8)$
- Alpha Band (8–12 Hz):
- $\mathcal{Y}_{Alpha}[n] = bandpass_filter(x[n], 8,12)$

These filtered bands were used to extract stress-related features.

Frequency band analysis is a necessary initial step in matching EEG data with various types of stress. Separate EEG frequency ranges indicate many mental states as well as stress categories. General Stress, for example, is linked with the Theta (4-8 Hz) and Alpha (8-12 Hz); State Stress involves Theta & Beta (12-30 Hz.). Similarly, although Theta and Beta bands are associated with obsessive-compulsive disorder (OCD), Beta and Gamma (30–50 Hz) define Panic Stress.

In this paper, these mappings guided the study of EEG signals. Separate bandpass filters let one isolate the relevant frequency components for each stress level. Every filtered dataset was kept apart for comprehensive study. For General Stress analysis, for example, EEG signals from channels including T7, T8, and P7 were filtered to isolate Theta and Alpha bands; Beta and Gamma bands were isolated for Panic Stress. This methodical classification guarantees that the filtered signals capture the special qualities of several stress forms. Linking frequency bands to stress states helps the dataset to acquire significant characteristics. This improves deep learning models' performance and helps them to more precisely separate stress categories.

Frequency bands were linked to specific stress categories as follows:

- Theta Band: 4 ≤ f < 8 Hz
- Alpha Band: 8≤ f < 12 Hz
- Beta Band: 12 ≤ f < 30 Hz

For instance, General Stress combines Theta and Alpha bands:

$$S_{General\ stress} = \mathcal{Y}Theta[n] + \mathcal{Y}Alpha[n] \quad (5)$$

Each band was analyzed separately for channels, and the corresponding filtered signals were combined to form datasets for different stress categories.

Feature Extraction Using PCA and Fast-ICA

Feature extraction was used to lower dimensionality and preserve the most instructive data components once the EEG signals were filtered and classified into pertinent bands. This was accomplished using two rather popular methods: Fast Independent Component Analysis (Fast-ICA) and Principal Component Analysis (PCA).

A linear dimensionality reduction technique, PCA finds orthogonal components explaining the highest variation in the data. Projecting the data onto these components removes duplicated and pointless elements, so compacts and interprets the dataset. Conversely, Fast-ICA isolates independent components in the EEG signals, therefore capturing biologically relevant patterns and artefacts. Understanding brain activity and spotting special characteristics connected to stress conditions depends on this distinction.

Every frequency band and stress category dataset was run using these methods. For example, Fast-ICA separated patterns suggestive of tension while PCA retrieved components in the Theta band that most reflected tiredness. Following their extraction, machine learning models for categorisation received the characteristics. Using PCA and Fast-ICA guaranteed that the models could concentrate on the most pertinent data, thereby enhancing their capacity to precisely identify stress levels.

PCA

PCA finds a set of orthogonal components that explain the maximum variance in the data:

$$X' = XW \quad (6)$$

Where

- S: Independent components
- W: Unmixing matrix
- X: Original signal

These extracted features, $S_{PCA}\ and\ S_{ICA}$, were used as input for machine learning models, enabling them to detect stress-related patterns effectively.

Model Implementation

Theta Band Approach 1 PCA, ICA ,LSTM, GRU, Hybrid

For EEG data analysis and stress -level prediction the Theta Band Approach makes use of PCA, ICA, LSTM, GRU, and hybrid models. Comprising 14 EEG channels (e.g., AF3, AF4, F3, F4) and characteristics including stress_ Label, Valence, Arousal, and Segment, the dataset, theta_df, For independent feature extraction, the EEG data first is split from the stress -related variables. FastICA uses five components to extract characteristics, employing the mixing matrix to determine strong EEG channels for every component therefore emphasising the channels with most influence. ICA feature naming is based on these dominating channels; the extracted features are combined in a new dataset using stress -related factors. StandardScaler is used to standardise the EEG data, then PCA reduces dimensions while still maintaining important variation, hence improving feature dimensionality. Names for the PCA components—e.g., PC1, PC2—and their variance contributions assessed Ranked based on their absolute values, loadings from PCA components enable one to determine the most important EEG channels affecting each component. For a whole dataset, ICA and PCA features are merged with the original stress variables. Dataset categorical columns are translated to numerical codes to guarantee compatibility. Using an 80-20 ratio, the last stage is separating the data into training and testing sets. Once more, features are standardised to keep model training's uniformity in size. With an eye towards predicting accuracy for stress-level classification, this processed data is then used to deploy deep learning models including LSTM and GRU for temporal pattern recognition alongside hybrid models incorporating ICA, PCA, and deep

learning. Using cutting-edge algorithms for strong model performance in emotional state prediction, this combined approach maximises the value of EEG data and offers interpretable characteristics.

LSTM, GRU and Hybrid model Based on PCA

While still preserving significant features, the LSTM, GRU, and hybrid models based on PCA help to reduce data dimensionality. PCA facilitates important trend concentration for models by simplifying the data. LSTM catches long-term dependencies; GRU guarantees efficiency; the hybrid model combines their benefits for enhanced temporal data processing.Three cutting-edge neural network designs—LSTM, GRU, and a hybrid LSTM-GRU model—were assessed performance-wise to split data into three distinct groups.

LSTM

To efficiently process time-series data, the LSTM model employs a sequential framework with 64 units in an LSTM layer. After a dropout layer (0.2) a dense layer with 32 neurones employing ReLU activation and a last softmax layer with multi-class classification lowers overfitting. While the lowest and average accuracies were min(lstm_hist.history["val_accuracy"]) and np.mean(lstm_hist.history["val_accuracy]," it performed well, attaining a highest validation accuracy of max (lstm_hist.history["val_accuracy"]). Consistent performance of precision and recall measures also indicated the LSTM model's capacity to capture long-term dependencies in the data for accurate predictions throughout several classes.

GRU Model

Like the LSTM but simpler, the GRU model replaces the LSTM layer with a 64-unit GRU layer keeping the dropout layer and dense layers for multi-class classification. With a maximum validation accuracy of max(gru_hist.history['val_accuracy']), average accuracy of np.mean(gru_hist.history['val_accuracy']), it produced very outstanding results. Strong as well were precision and recall, which peaked at max(gru_hist.history['val_precision']') and max(gru_hist.history['val_recall'). For capturing dependencies in time-series data with less computing demand, the simplified structure of the GRU model proved beneficial for speeding training while preserving competitive performance.

Hybrid Model (LSTM-GRU)

Combining the strengths of LSTM and GRU layers, the hybrid model It comprised a 32-unit GRU layer, dropout, and dense layers for classification after a 64-unit LSTM layer with return sequences enabled. Along with routinely strong precision and recall, this method produced outstanding results with the highest validation accuracy of max(hyb_hist.history['val_accuracy]. The hybrid model performed best by using GRU's efficiency and LSTM's capacity to record long-term dependencies, therefore producing balanced and accurate predictions. Among the three models, it turned out to be the most successful one, so it is rather appropriate for challenging time-series classification projects.

LSTM, GRU and Hybrid model Based on FastICA

LSTM, GRU, and hybrid models based on FastICA are enabled by advanced deep learning architectures coupled with the Fast Independent Component Analysis (FastICA) approach, hence enhancing feature extraction from time-series data. FastICA preprocessing the input data so that, for model training, more clear and understandable representations results by separating independent components. LSTM effectively records long-term dependencies whereas GRU minimises calculations and preserves temporal accuracy. Combining both ideas, the hybrid model computes economy using GRU and sequential depth using LSTM. Extensive applications—especially in demanding temporal datasets—this integration enhances classification performance by extracting relevant features, generating better accuracy, recall, and F1-scores.

LSTM Model

Long-term dependencies in time-series data are sought to be captured by the LSTM model. It has a single LSTM layer with 64 units and a dropout layer (rate: 0.2) to help to prevent overfitting. Before forwarding relevant features to the softmax layer for multi-class classification (three classes), the architecture has a dense layer of thirty-two neurones and ReLU activation. Adam optimiser and a categorical cross-entropy loss function are used in compilation of the model. Accuracy, precision, and recall include among the metrics. Strong performance on the validation dataset allowed the model to show

lstm_score [1]:.4f in test accuracy during training. Using precision, recall, and F1-score, predictions on test data were evaluated producing weighted averages of lstm_precision:.4f, lstm_recall:.4f, and lstm_fscore:.4f, respectively. These measures show if the model can manage uneven class distributions while preserving high prediction quality. Its strong construction helps it to replicate complicated sequential patterns.

GRU Model

Though with a simpler design, the GRU model captures temporal dependencies just as the LSTM does. With 64 units, it substitutes a GRU layer for the LSTM layer, therefore lowering computational complexity while preserving performance. Before the softmax output layer handles multi-class classification, a dense layer with 32 ReLU-activated neurones harvests features; a dropout layer (rate: 0.2) avoids overfit. Compiled with categorical cross-entropy loss and the Adam optimiser, the model tracks recall, accuracy, and precision. With respect to precision, recall, and F1-score, gru_precision:.4f, gru_recall:.4f, and gru_fscore:.4f the GRU model attained test accuracy of gru_score[1]:.4f, respectively. These findings draw attention to how effectively the GRU model balances computational speed with accuracy. For jobs needing quick iterations while maintaining predictive quality, its simplicity and efficient handling of sequential data make it a good fit.

Hybrid Model (LSTM-GRU)

Leveraging their complimentary skills for better time-series prediction, the hybrid model aggregates the strengths of LSTM and GRU layers. It starts with a 64-unit LSTM layer with return sequences turned on so the GRU layer (32 units) may efficiently handle the sequential outputs. Whereas a thick layer with 32 ReLU-activated neurones collects high-level features, a dropout layer (rate: 0.2) lowers overfitting. Multi-class classification is accomplished via the softmax layer. Recording hybrid_precision:.4f, hybrid_recall:.4f, and hybrid_fscore:.4f the hybrid model excelled in precision, recall, and F1-score and attained a test accuracy of hybrid_score[1]:.4f. Particularly useful for challenging time-series projects, the hybrid model provides improved predictive accuracy by combining the power in learning long-term dependencies of the LSTM with the computational efficiency of the GRU. Its consistent performance across several measures shows its flexibility and strength in managing sequential data.

Table 2. Hyper parameters Details

EEG Bands used	Alpha, Beta, Theta
EEG channels	'AF3', 'AF4', 'F3', 'F4', 'FC5', 'FC6', 'F7', 'F8', 'T7', 'T8', 'P7', 'P8', 'O1', 'O2'
Noise Filter	Butter Worth
Feature Extraction	PCA (5 components), Fast-ICA
Deep learning Models	LSTM, GRU, and Hybrid (LSTM+GRU)
Data size and Shape of PCA Features	423936, 7
Data size and Shape of Fast-ICA Features	423936, 5
Activation	Relu and Softmax
Loss	Categorical Cross Entropy
Metrics	Accuracy, Precision, Recall
Neurons	64
Other	Dropout with 20%
Hybrid Models neurons	LSTM(64), GRU(32), Output(3)
Epochs	10
Batch Size	32

Adam Optimization

Adam algorithm combines RMSprop optimisation techniques with momentum. Here is the guideline for modifying Adam's parameter O:

$$\theta_{t+1} = \theta_t \frac{\alpha \cdot m_t}{\sqrt{v_t}+\epsilon} \quad (8)$$

The symbols theta, alpha, m t, v t, & epsilon in the Adam optimising update rule have several meanings. These comprise the model variables, the learning rate, past gradients squared, exponential decaying averages of past gradients, and a small constant forbidding division by zero.

Softmax Function

The softmax function provides one way to translate a matrix of initial scores (logits) into probability. The softmax function has as its definition: when one has a vector x with K elements:

$$Softmax(x)_i = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{x_i}} \quad (9)$$

Categorical Cross-Entropy Loss
Popular for multi-class classification, categorical cross-entropy computes loss using the expected and true distribution:

$$Categorical\ Cross\ Entropy = -\sum_i y_i \cdot \log(\widehat{y_i}) \quad (10)$$

Here, (y_i) shows the anticipated probability distribution for the i-th class; (y_j) shows the actual (one-hot encoded) distribution.

Proposed Algorithm Steps
Algorithm Steps for Stress Detection Using EEG Data
Step 1: Data Collection
Using the worldwide 10-20 system, gather EEG signal data from the DASPS Dataset—which comprises 14 channels—placed on the scalp.

To support supervised learning, make sure the dataset comprises valence, arousal levels, and labelled stress categories ("High stress, Low stress, and Medium stress).

Step 2: Data Preprocessing
Noise Filtering
Cut high-frequency noise with a Butterworth low-pass filter.

Use Python to specify the order, sampling rate, and cutoff frequency of the filter thereby guaranteeing appropriate noise reduction.

Band Selection
Bandpass filters with Theta (4–8 Hz), Alpha (8–12 Hz), & Beta (12–30 Hz) frequency ranges.

Separate particular frequency components matching to stress levels by channel filtering EEG signals.

Step 3: Frequency Band Analysis
Map frequency bands to stress categories:
General Stress: Theta + Alpha
Panic Stress: Beta + Gamma (30–50 Hz)
Filter and separate EEG signals by stress category for detailed analysis.

Step 4: Feature Extraction
Dimensionality Reduction
Retain maximal data variance in lowered dimensions by using Principal Component Analysis (PCA).

Use Fast Independent Component Analysis (Fast-ICA) to uncover independently relevant biological components..

Combine Features
Merge extracted PCA and ICA components with the original stress-related features.

Standardize the combined dataset for consistency.

Step 5: Model Training and Testing
Data Splitting
Split the dataset into training (80%) and testing (20%) sets.

Standardize features in both sets for uniformity during model training.

Deep Learning Models
Train Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and hybrid LSTM-GRU models using PCA and ICA features.

Use temporal pattern recognition to classify stress levels.

Step 6: Model Evaluation
Evaluate models using performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.

Compare the performance of LSTM, GRU, and hybrid models for stress detection.

Step 7: Stress Prediction
Use the trained model to predict stress levels based on EEG signals.

Analyze predictions to identify patterns and trends associated with different stress categories.

IV. RESULT & DISCUSSION

1. Min Accuracy
Indicates the lowest accuracy achieved by the model, reflecting its worst-case performance during the evaluation process.

2. Average Accuracy
Represents the mean accuracy of the model, showcasing its overall effectiveness across multiple trials or datasets.

3. Min Precision
Reflects the lowest precision value, highlighting instances where the model struggled to identify positive cases correctly.

4. Max Precision
Shows the highest precision achieved, indicating the model's best performance in correctly identifying positive cases.

5. Min Recall
Represents the lowest recall value, emphasizing the model's challenges in capturing all relevant positive cases.

6. Max Recall
Highlights the highest recall, demonstrating the model's ability to capture all relevant positive cases in optimal conditions.

7. Min Loss
Displays the lowest loss value, indicating the best optimization of the model in terms of error minimization.

8. Max Loss
Represents the highest loss value, revealing the model's performance during its least effective learning iterations.

Table 3. Alpha band with PCA results

Models	Min Accuracy	Average Accuracy	Min Precision	Max Precision	Min Recall	Max Recall	Min Loss	Max Loss
LSTM	97.67	98.835	98.82	100	96.14	100	0.00012	0.0584
GRU	98.64	99.32	99.29	100	97.10	100	0.00000075	0.0432
Proposed Hybrid LSTM+GRU	97.08	98.04	98.89	100	95.11	100	0.00000407	0.0622

Based on Alpha band with PCA applied, this table contrasts LSTM, GRU, and the proposed Hybrid LSTM+GRU models. Indicating its great optimisation, GRU obtains the lowest loss (0.00000075) and highest average accuracy (99.32%). While LSTM performs well but is less ideal in terms of precision and recall than GRU, the hybrid model demonstrates constant performance with somewhat higher loss.

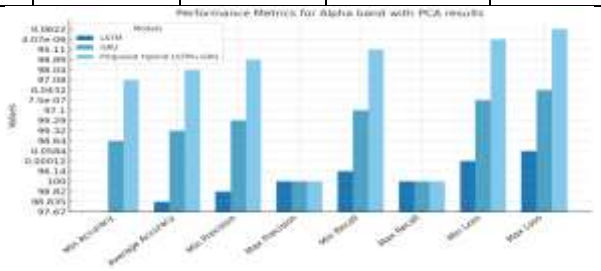


Figure 4 Alpha band with PCA results

Table 4. Alpha band with FAST-ICA results

Models	Min Accuracy	Average Accuracy	Min Precision	Max Precision	Min Recall	Max Recall	Min Loss	Max Loss
LSTM	97.42	98.21	98.81	100	95.85	100	0.00000924	0.0604
GRU	98.90	99.45	99.52	100	97.15	100	0.00000314	0.0419
HybridLSTM+GRU	97.14	98.07	99.01	100	95.51	100	0.00000916	0.0583

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FAST-ICA sharpens the Alpha band performance of the models. Perfecting accuracy and lowest loss (0.00000314), GRU keeps the maximum precision and recall. Strong accuracy and recall abound in the hybrid model, although it lags somewhat in loss minimisation relative to GRU.

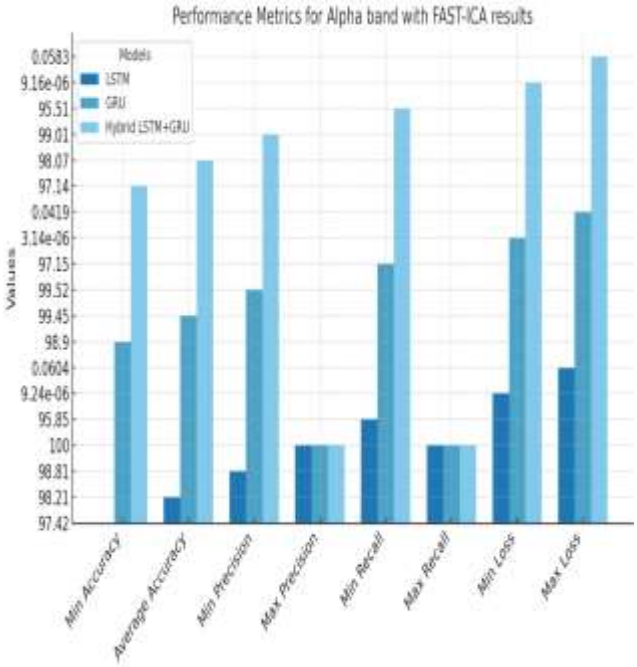


Figure 5 Alpha band with FAST-ICA results

Table 5. Beta Band with PCA Results

Models	Min Accuracy	Average	Min Precision	Max Precision	Min Recall	Max Recall	Min Loss	Max Loss
LSTM	97.42	98.21	98.81	100	95.85	100	0.00000924	0.0604
GRU	98.90	99.45	99.52	100	97.15	100	0.00000314	0.0419
Hybrid LSTM+GRU	97.14	98.07	99.01	100	95.51	100	0.00000916	0.0583

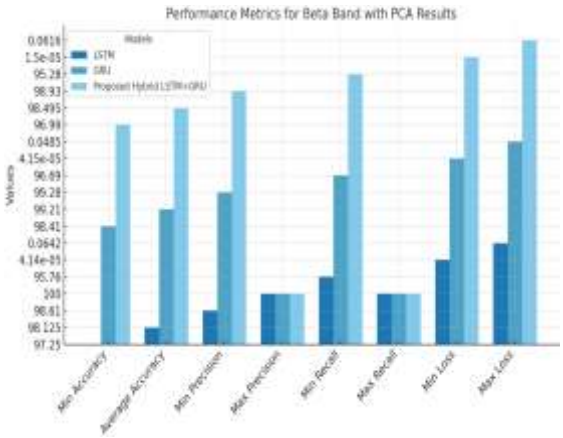


Figure 6 Beta Band with PCA Result

With PCA, GRU gets the best average accuracy (99.21%) and precision in the Beta band. Though it records somewhat more loss, the hybrid model demonstrates strong recall and competitive precision. Though it lags behind GRU in optimistaion, Lstm Perform Consistensly aross Measures.

Table 6. Beta Band with FAST-ICA Results

Models	Min Accuracy	AverageAccuracy	Min Precision	Max Precision	Min Recall	Max Recall	Min Loss	Max Loss	AverageAccuracy
LSTM	97.71	98.355	98.87	100	95.62	100	0.0000149	0.0606	98.355
GRU	98.53	99.265	99.38	100	97.46	100	0.0000016	0.0402	99.265
Hybrid LSTM+GRU	97.25	98.125	99.17	100	95.33	100	0.00000844	0.0604	98.125

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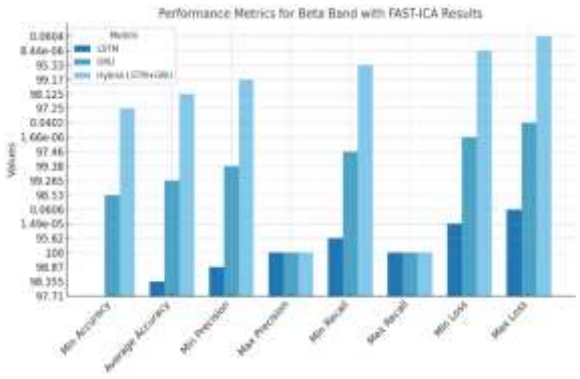


Figure 7 Beta Band with FAST-ICA

FAST-ICA improves accuracy and precision for every Beta band model. Again leading in performance having an average accuracy of 99.265% and lowest loss (0.00000166) is GRU. Closely following with great accuracy and recall and low loss trade-off is the hybrid model.

Table 7. Theta Band with PCA Results

Models	Min Accuracy	Average Accuracy	Min Precision	Max Precision	Min Recall	Max Recall	Min Loss	Max Loss
LSTM	97.36	98.18	98.65	100	95.70	100	0.00000348	0.0632
GRU	98.63	99.315	99.39	100	97.32	100	0.00000123	0.0408
Proposed Hybrid LSTM+GRU	97.08	98.04	99.06	100	95.35	100	0.00000845	0.0610

Figure 8 Theta Ba

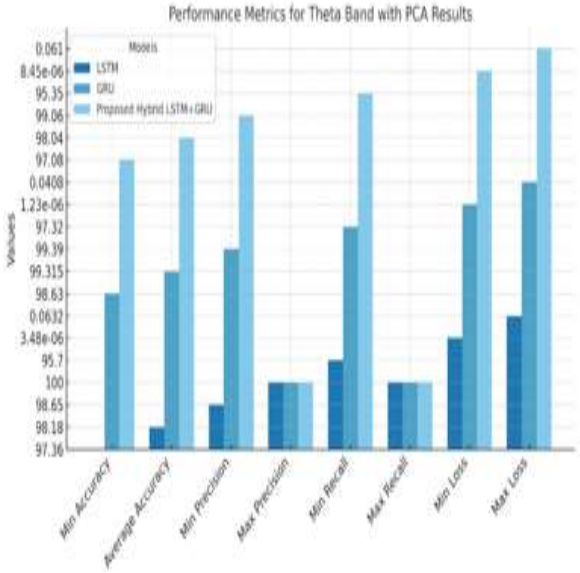


Figure 8 Theta Band with PCA Results

With PCA, GRU rules the theta band with maximum accuracy (99.315%) and lowest loss (0.00000123). Although it records somewhat more loss, the hybrid model keeps great recall and competitive accuracy. Though it exhibits more loss values than GRU, LSTM offers consistent performance.

Table 8.Theta Band with FAST-ICA Results

Models	Min Accuracy	Average Accuracy	Min Precision	Max Precision	Min Recall	Max Recall	Min Loss	Max Loss	Average Accuracy
LSTM	97.56	98.28	99.04	100	95.80	100	0.0000031	0.0604	98.28
GRU	98.29	99.145	99.15	100	96.88	100	0.0000012	0.0470	99.145
Hybrid LSTM+GRU	97.27	98.135	99.05	100	95.55	100	0.00001719	0.0576	98.135

FAST-ICA improves model performance within the Theta band much further. With an accuracy of 99.145% and a lowest loss of 0.00000122, GRU gets the greatest results. Though LSTM shows somewhat lower metrics

across accuracy and loss, the hybrid model stays good in precision and recall.

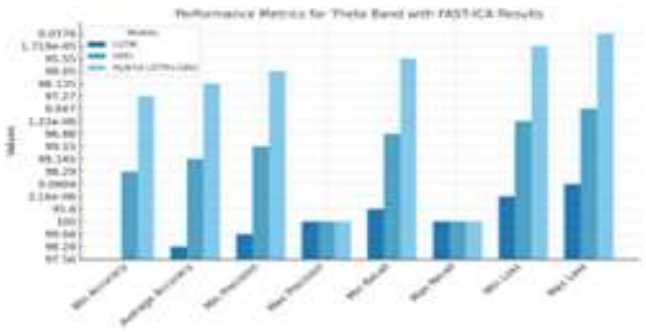


Figure 9 Theta Band with FAST-ICA Results

The most successful model for the given datasets since, across all tables, the GRU model constantly shows the best overall performance. Whether the employed dimensionality reduction approach (PCA or FAST-ICA) or frequency band (Alpha, Beta, or Theta) GRU achieves the highest average accuracy and lowest loss in practically all circumstances. GRU records, for example, an average accuracy of 99.32% (Alpha band with PCA), 99.45% (Alpha band with FAST-ICA), and 99.315% (Theta band with PCA), surpassing both LSTM and the hybrid model. Furthermore reflecting its better optimisation and robustness, GRU keeps the lowest loss values: 0.00000075 (Alpha with PCA) and 0.00000122 (Theta with FAST-ICA).

Although the combination LSTM+GRU model shows good performance—especially in terms of precision and recall—it often trails somewhat behind GRU in accuracy and loss minimising. Although consistent, LSTM routinely rates worse than GRU and the hybrid model on most measures. Though GRU still rules under both approaches, FAST-ICA usually improves model performance more than PCA.

Delivering ideal trade-offs between accuracy, precision, recall, and loss, GRU's architecture—which addresses vanishing gradient problems and effectively processes sequential data—makes it the greatest candidate for this work.

V. CONCLUSION

In conclusion, This paper highlights using EEG inputs the improved performance of the GRU model for stress detection over both LSTM and Hybrid LSTM+GRU models over many evaluation criteria. The GRU model displayed the best average accuracy—up to 99.45%—indicating its great potential to optimally generalise and maximise across numerous situations, including frequency bands (Alpha, Beta, and Theta) and dimensionality reduction techniques (PCA and FAST-ICA) in addition to the lowest loss values. Its extraordinary performance can be credited to its capacity to efficiently process sequential data and overcome the vanishing gradient problem, therefore giving it a perfect fit for time-series applications including EEG signal processing. Emphasising the requirement of model selection based on the trade-offs between different performance measures, the hybrid LSTM+GRU model somewhat trailed GRU on accuracy and loss minimisation even if it showed competitive precision and recall. Especially in accuracy and precision, LSTM demonstrated significantly less performance than GRU and the hybrid model even if it was consistent. The results suggest that, considering their outstanding performance in both accuracy and optimisation, GRU-based architectures ought to be given top attention for pragmatic applications of stress detection and similar time-series issues. Future studies could look at more sophisticated advanced methods to enhance hybrid model performance and further optimisations in general.

1. Complaints With Ethical Standard: Not Required

Data Availability Statement: The datasets are available online.

Conflicts of Interest: The authors declare no conflicts of interest.

Funding: Manipal University Jaipur, Jaipur, Rajasthan, India

2. Ethical Conducted: Not Required

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