# Mental Stress Classification Using Multivariate Analysis of Variance with Bidirectional Long Short-Term Memory Model

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## ABSTRACT

**In humans, stress is a natural reaction to pressure, and when stress increases, the risk of mental health issues also increases. Misclassification can be caused by redundancy in certain physiological and behavioral features. To overcome this limitation, this study performs a Multivariate Analysis of Variance (MANOVA) based feature selection method, along with a Bidirectional Long Short-Term Memory (Bi-LSTM) model for efficient stress classification. The proposed MANOVA technique evaluates multiple dependent variables simultaneously, capturing correlations between physiological features to identify the most informative for the classification of mental stress. The Bi-LSTM model processes stress-related physiological signals, including heart rate and skin conductance, both forward and backward, effectively capturing long-term dependencies that help improve classification. Initially, ElectroCardioGram (ECG) signal data were obtained from two benchmark datasets. Then, label encoding techniques were employed for converting categorical features into numerical ones, and normalization was used to scale the data into a uniform range. The proposed stress classification model was experimentally evaluated on the WESAD and SWELL-KW datasets, achieving accuracies of 99.50% and 99.80%, respectively, outperforming existing approaches.**

***Keywords-bidirectional long short-term memory; electrocardiogram; label encoding; multivariate analysis of variance; stress classification***

## I. INTRODUCTION

Stress is defined as a physical, mental, or emotional reaction, categorized into two types, long-term and short-term, both associated with depressive conditions triggered by specific situations [1]. Stress is caused by various biological, psychological, environmental, and sociocultural factors that affect individuals psychologically and influence their ability to perform optimally [2, 3]. In the past, physiologists and physicians have used various clinical, experimental, and psychological methods to analyze stress levels [4]. Each technique analyzes and evaluates stress differently, based on how individuals make decisions in response to psychological, physical, or behavioral changes [5, 6]. In addition, stress levels are evaluated using a metric known as Heart Rate Variability (HRV), which measures fluctuations in heartbeat intervals to assess an individual's physiological state [7-9]. A high HRV represents healthier nervous system function, while a low HRV indicates higher stress levels [10]. HRV is measured using several techniques, including Photoplethysmography (PPG), accelerometers, and Electrocardiography (ECG). However, HRV features alone do not accurately reflect stress levels, as HRV values are influenced by various physical and mental health factors. In existing research, ML algorithms have been employed to identify and analyze stress levels using HRV, but these approaches often fail to precisely assess stress levels and are unable to adapt to heart rate variations. Hence, DL-based models have been increasingly used to analyze mental stress, particularly in applications involving detection, classification, and prediction. Various DL algorithms have been applied to stress detection and classification tasks, allowing for simplified categorization of stress types [11, 12]. However, feature selection methods used in existing models often select irrelevant features and do not capture correlations between features, which are essential for accurate classification of mental stress. Existing research on mental stress classification has been conducted, and the limitations of prior algorithms are analyzed in the following sections.

In [13], a boosting approach was proposed for the detection of mental stress. To efficiently classify stress levels, the boosting network utilized respiration rate as a key biomarker, which helped improve accuracy. However, this model relied heavily on specific data and did not focus on other important factors that caused misclassification. In [14], a Sequential Feature Extraction (SFE) and multi-class classifier model was used to understand human emotions and identify stress. This study examined several models, combining SFE with Random Forest (RF), K-Nearest Neighbor (KNN), Logistic Regression (LR), and Support Vector Classifier (SVC) for feature extraction and accurate classification of stress levels. However, the suggested SFE-based technique selected the most relevant features, but also discarded some features with significant information, considering them less prominent, which reduced the model's ability to accurately capture stress patterns. In [15], a stress recognition model was based on a bootstrapped ensemble DL algorithm. The ensemble model utilized CNN and Long Short-Term Memory (LSTM) to recognize and classify stress levels, capturing both spatial and temporal patterns in physiological data, thereby improving overall classification performance.

In [16], a stress classification model used time-domain features with various ML classifiers, such as RF, Decision Tree (DT), and KNN, along with a Multilayer Perceptron (MLP) model. Features were selected using the Information Gain (IG) technique. However, feature selection based on IG selected redundant features with less correlation, which affected stress classification. In [17], a multi-class stress detection model utilized HRV from ECG signals. The primary advantage of this classification model was that it utilized a one-dimensional CNN (1D-CNN) model for feature extraction, which helped precisely differentiate stress levels. However, feature selection based on the ANOVA technique failed to capture correlations between features and selected inappropriate ones, which led to inaccurate stress classification.

To address this issue, this study uses a Multivariate Analysis Of Variance (MANOVA)-based feature selection model to determine the correlations between features and improve the classification results on mental stress. The primary contributions of this study are as follows:

- Preprocessing is performed using label encoding to convert categorical features into numerical ones and improve overall classification performance.
- MANOVA evaluates multiple dependent variables simultaneously and captures the correlations between physiological features to identify the most informative and discriminative to improve mental stress classification and model performance.
- The Bi-directional LSTM (Bi-LSTM) model effectively processes stress-related physiological signals related to heart rate and skin conductance. This model efficiently captures long-term dependencies by processing data in both the forward and backward directions, thereby enhancing stress classification performance.

## II. METHODOLOGY

The objective of this research is to efficiently classify stress using the proposed Bi-LSTM-based classification model. The proposed framework involves four phases: data acquisition, preprocessing, feature selection, and classification. Figure 1 presents an overview of the proposed mental stress classification system.

### A. *Dataset Acquisition*

Benchmark datasets are used to train and test the proposed classification model to accurately analyze mental stability and classify stress.

### 1) *WESAD Dataset*

In this dataset, physiological changes were recorded using devices attached to two locations on each subject to monitor their physiological responses and potential abnormalities. The dataset comprises data from 15 subjects. A total of 12 biomarkers were recorded, among which six are considered in this study. These measurements were collected over a period of two hours using chest-worn (RespiBAN Professional) and wrist-worn (Empatica E4) Internet of Medical Things (IoMT) devices. The WESAD dataset [18] includes three distinct emotional states: neutral, stress, and amusement. This represents an advancement over earlier datasets that primarily focused on two affective states: stress and no stress.

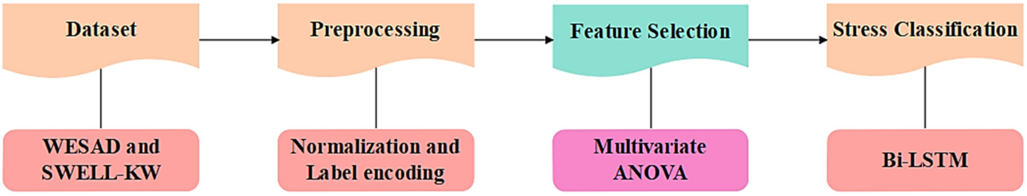

Fig. 1. Proposed stress classification model using MANOVA-BiLSTM from data collection to stress level classification

### 2) SWELL-KW Dataset

In the SWELL-KW dataset [19], data were collected from various sources, including body postures using a Kinect three-dimensional (3D) sensor, computer usage logs, heart rate (and its variability), skin conductance from wearable body sensors, and facial expressions captured from camera recordings. Participants were subjected to two types of stress-inducing conditions: time pressure and email interruptions. The dataset includes HRV values that are used to estimate stress levels for each participant. These stress levels are categorized into three distinct classes: no stress, time pressure, and interruption.

## B. Data Preprocessing

The data is preprocessed to convert it into a structured format suitable for accurate classification. Preprocessing is a critical step in the proposed stress classification framework, as raw stress-related data often contain inconsistencies, such as varying heart rates and irrelevant information from behavioral and physiological signals.

### 1) Label Encoding

Label encoding converts categorical features, such as class labels, into numerical values to allow the classification model to interpret and process them effectively.

### 2) Normalization

Data vary in scale due to differing units and ranges across feature types, such as heart rate and skin conductance. This variation may cause the model to focus on features with larger numerical values.

## C. Proposed Feature Ranking and Extraction

The preprocessed features were passed to ANOVA, which is a widely used statistical analysis test to compare the means of two or more classes. ANOVA can be used for feature selection by evaluating the statistical significance of each feature's relationship with the target variable. This study used an ANOVA-based statistical technique to rank features according to their F-scores, where features with high F-scores indicate a stronger relationship. Based on the predefined threshold, the extracted features, ordered from the top-ranked ones, are selected and fed to the classification model. ANOVA helps to select significant features that contain distinct information across classes. This technique selects the most relevant features and eliminates those with redundant information, thus minimizing computational complexity and avoiding overfitting. In addition, ANOVA-based feature selection provides a statistical value that justifies the importance of certain features, helping to understand which physiological and behavioral signals contribute more to enhancing stress classification. The ANOVA model ranks and selects features using the F-score.

$$f_{score} = \frac{MSSB}{MSSW} \tag{1}$$

where $f_{score}$ denotes feature significance, $MSSB$ represents the mean value of the Sum of Squares Between groups (SSB), and $MSSW$ represents the Mean value of the Sum of Squares Within groups.

However, the ANOVA model evaluates each feature independently, paying less attention to interactions between heart rate and skin conductance, resulting in sub-optimal feature selection and misclassification. To solve this problem, an improved Multivariate ANOVA (MANOVA) technique was used to effectively learn feature correlations. In MANOVA, each feature is denoted as a vector $X_{ijp}$, where $i$ denotes the index of an observation, $j$ indicates the category, and $p$ represents the features within a group. The Total Sum of Squares and Cross Product (TSSCP) is given by:

$$TSSCP = \sum_{j=1}^{k} \sum_{i=1}^{n} \left(X_{ij} - \overline{X_T}\right)\left(X_{ij} - \overline{X_T}\right)^T \tag{2}$$

$$TSSCP = \sum_{j=1}^{k} \sum_{i=1}^{n} \left[\left(X_{ij} - \bar{X}_J\right) + \left(\bar{X}_J - \overline{X_T}\right)\right]\left[\left(X_{ij} - \bar{X}_J\right) + \left(X_{ij} - \overline{X_T}\right)^T\right] \tag{3}$$

$$TSSCP = \sum_{j=1}^{k} nj\left(\bar{X}_J - \overline{X_T}\right)\left(\bar{X}_J - \overline{X_T}\right)^T + \sum_{j=1}^{k} \sum_{i=1}^{n} \left(X_{ij} - \overline{X_T}\right)\left(X_{ij} - \overline{X_T}\right)^T \tag{4}$$

$$TSSCP = H + E \tag{5}$$

where $E$ denotes the error matrix and $H$ represents the hypothesis matrix. The F-score for the proposed MANOVA model is calculated using Pillai's trace value, which is obtained from the $H$ and $E$ matrices, mathematically formulated as:

$$f_{score} = trace\left(\frac{H}{H+E}\right) = \sum_{i=1}^{q} \frac{\lambda_i}{1+\lambda_i} \tag{6}$$

where $\lambda_i$ denotes eigenvalues and $q$ represents non-zero generalized values. By utilizing the above equation, $f_{score}$ is evaluated for each feature set, and these values are then normalized to a range between 0 and 1. Based on the obtained $f_{score}$, the p-value is evaluated for all ranked features. Features with a p-value less than 0.05 are selected and fed to train the classification model and effectively categorize mental stress levels. The proposed MANOVA technique evaluates multiple dependent variables simultaneously and captures the correlations between physiological features to identify the most informative and discriminative features and improve the performance of mental stress classification. The process of feature ranking and selection using the proposed MANOVA technique is represented by the following steps.

- Step 1 - Feature clustering: Initially, all input features are categorized into various groups, each representing a specific factor related to emotion.
- Step 2 - Applying MANOVA: For each group, the proposed MANOVA method is applied to evaluate how well the features distinguish between different stress emotions. When compared to traditional ANOVA, which evaluates features individually, the proposed method evaluates them collectively as a multivariate vector.
- Step 3 - Estimation of MANOVA $f_{score}$: The statistical test-based feature selection technique uses the $f_{score}$ to assess feature importance. In the proposed MANOVA technique, Pillai's trace is used to calculate the $f_{score}$.
- Step 4 - $f_{score}$ normalization: After calculating the F-scores, each group's score is normalized, using min-max

normalization, within the range [0, 1]. This normalized score represents the relative importance of each group in stress classification.

- Step 5 - Feature allocation based on ranks: The number of features selected from each group is determined based on the normalized MANOVA scores. Features with higher MANOVA scores contribute more significantly to stress classification and are fed into the classification model.

This feature ranking-based selection process helps identify the most important factors for stress level classification. The proposed MANOVA model ranks the features according to how strongly they differ across stress emotion categories, enabling effective differentiation between stress and non-stress classes.

### *D. Selected Important Features for Stress Level Classification*

The SWELL-KW dataset has a total of 36 features, comprising both physiological and behavioral data. Of these, 29 features containing significant information are retained, while the remaining are eliminated. Selected features include skin conductance level, heart rate variability, and behavioral indicators, such as mouse usage speed, typing speed, and skin temperature. These features reflect key physiological and behavioral responses associated with stress, such as sympathetic nervous system activation, increased perspiration, irregular typing patterns, and reduced peripheral temperature, all of which support accurate stress level classification.

The WESAD dataset has 67 features that encompass both physiological and behavioral attributes. Of these, 54 features containing stress-related information are retained, while features deemed irrelevant are discarded. The selected features include skin conductance, respiration rate, skin temperature, and acceleration-based indicators. These features provide essential information, such as emotional state fluctuations, rapid breathing, temperature variation due to blood flow changes, and increased physical movement under stress, enabling the model to classify mental stress levels with high precision. The selected features from both datasets contain critical physiological and behavioral signals that allow the classification model to effectively distinguish between stress and non-stress conditions.

### *E. Stress Classification*

The selected features from the MANOVA technique were fed as input to a stress classification model based on Bi-LSTM, which is an advancement over traditional RNN and LSTM models [20]. The Bi-LSTM model consists of two LSTM blocks that capture stress-related information in both forward and backward directions. Figure 2 illustrates the architecture of the Bi-LSTM-based stress classification model. This approach considers both past and future contexts for improved model accuracy.

The features fed as input to the Bi-LSTM model are denoted as $x_{t-1}$, $x_t$, and $x_{t+1}$. An advantage of the Bi-LSTM method is that it processes feature sequences efficiently and retains temporal information, making the model well-suited for continuous monitoring of stress status. The Bi-LSTM model estimates the overall output stress status based on (7).

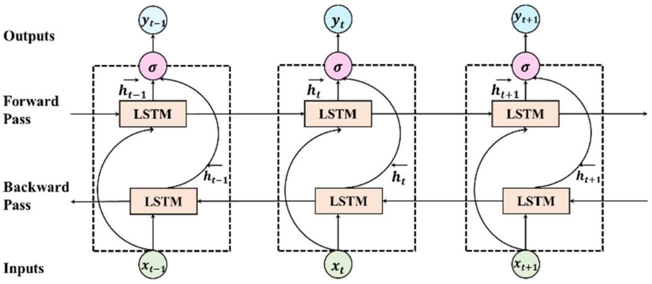

Fig. 2. Bi-LSTM model for mental stress level classification.

$$h_t = \sigma\left(W_h \times \left[\overrightarrow{h_t}, \overleftarrow{h_t}\right] + b_h\right) \tag{7}$$

where $h_t$ denotes the output layer, $W_h$ and $b_h$ represent weight and bias, respectively, and $\sigma$ indicates the sigmoid activation function. The LSTM block consists of three important gates and a memory cell, which helps process the features efficiently and provide accurate results. The important gates of the LSTM model are the input, forget, and reset gates, along with a memory cell. These gates decide which information should be considered and which should be forgotten for processing classification. In addition, the gates control the information that should be added to the memory cell and the output of the memory cell. The mathematical representations of these LSTM gates and memory cells are expressed in (8)-(13):

$$i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \tag{8}$$

$$f_t = \sigma\left(W_f \times [h_{t-1}, x_t] + b_f\right) \tag{9}$$

$$\tilde{C}_t = tanh(W_c \times [h_{t-1}, x_t] + b_c) \tag{10}$$

$$C_t = f_t \times C_{t-1} + i_t\tilde{C}_t \tag{11}$$

$$o_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \tag{12}$$

$$h_t = o_t \times tanh(C_t) \tag{13}$$

where $i_t$, $f_t$, $o_t$, and $C_t$ denote the input, forget, output gates, and memory cell, $\sigma$ and $tanh$ are activation functions, $W_i$, $W_f$, $W_o$, and $W_c$ represent weights for input, forget, output gates, and memory cell, respectively, and $b_i$, $b_f$, $b_o$ and $b_c$ are the biases for the input, forget, output gates, and memory cell, respectively. The bidirectional nature of Bi-LSTM captures temporal relationships by leveraging future context, enhancing stress level classification. The backpropagation process fine-tunes the model using error signals from both directions, enabling effective learning of complex temporal dependencies, such as fluctuations in physiological data. This bidirectional processing helps capture continuous physiological and behavioral signals, such as body temperature, heart rate, and motion, thereby improving the accuracy of stress classification. Compared to the traditional LSTM model, Bi-LSTM is better suited for recognizing gradual transitions between baseline, relaxed, and stress states. Moreover, Bi-LSTM can retain long-term patterns and identify fine-grained variations, such as changes in heart rate and skin conductance, which are strongly associated with stress. Therefore, the features selected by the proposed MANOVA technique, combined with classification via the Bi-LSTM model, significantly enhance mental stress level classification.

## III. RESULTS AND DISCUSSION

The proposed model was developed using Python 3.9 in a system with Windows 10, 16 GB RAM, and an i5 processor. Table I presents the parameter settings of the proposed MANOVA-Bi-LSTM model used for mental stress level classification.

TABLE I. PARAMETER SETTINGS OF THE PROPOSED MANOVA – BI-LSTM MODEL FOR MENTAL STRESS CLASSIFICATION

| Parameters | Values |
|---|---|
| Batch size | 32 |
| Loss function | Categorical cross entropy |
| Learning rate | 0.001 |
| Optimizer | Adam |
| Epochs | 100 |

To estimate the effectiveness of the proposed method in the classification, average accuracy, recall, precision, and F1-score were utilized, which are mathematically formulated as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{14}$$

$$Precision = \frac{TP}{TP+FP} \tag{15}$$

$$Recall/Sensitivity = \frac{TP}{TP+FN} \tag{16}$$

$$F1-Score = 2 \times \frac{Precision \times Sensitivity}{Precision+ensitivity} \tag{17}$$

where $TP$ and $FP$ denote True Positives and False Positives, and $TN$ and $FN$ represent True Negatives and False Negatives.

### A. *Qualitative and Quantitative Analysis*

The performance of the proposed MANOVA-based technique was compared against other state-of-the-art feature selection methods, including Principal Component Analysis (PCA), Consistency-based Discriminative Analysis (CDA), and conventional ANOVA. Table II summarizes the performance evaluation of the proposed MANOVA against these feature selection techniques. The proposed MANOVA technique enhances feature selection, leading to improved stress classification by effectively capturing correlations among features.

TABLE II. PERFORMANCE EVALUATION OF THE PROPOSED MANOVA WITH DIFFERENT FEATURE SELECTION TECHNIQUES

| Methods | Datasets | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|---|
| PCA | EEG | 92.45 | 92.3 | 92.5 | 92.4 |
| | SWELL | 91.87 | 91.61 | 91.83 | 91.72 |
| | WESAD | 91.12 | 90.92 | 91.05 | 90.98 |
| CDA | EEG | 93.1 | 92.95 | 93.15 | 93.05 |
| | SWELL | 92.91 | 92.81 | 92.86 | 92.84 |
| | WESAD | 92.5 | 92.31 | 92.42 | 92.36 |
| ANOVA | SWELL | 93.72 | 93.56 | 93.61 | 93.58 |
| | WESAD | 93.2 | 93.02 | 93.1 | 93.06 |
| MANOVA | SWELL | 99.80 | 99.73 | 99.78 | 99.76 |
| | WESAD | 99.50 | 99.13 | 99.41 | |

TABLE III. PERFORMANCE EVALUATION OF THE BI-LSTM-BASED STRESS CLASSIFICATION MODEL WITH DIFFERENT DL-BASED CLASSIFIERS

| Methods | Datasets | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|---|
| RNN | SWELL | 94.52 | 94.31 | 94.13 | 94.22 |
| | WESAD | 93.8 | 93.61 | 93.72 | 93.66 |
| LSTM | SWELL | 95.87 | 95.61 | 95.42 | 95.51 |
| | WESAD | 95.1 | 94.92 | 94.85 | 94.88 |
| GRU | SWELL | 96.01 | 95.81 | 95.61 | 95.71 |
| | WESAD | 95.68 | 95.41 | 95.53 | 95.47 |
| Bi-GRU | SWELL | 95.51 | 95.21 | 95.02 | 95.12 |
| | WESAD | 95 | 94.75 | 94.89 | 94.82 |
| Proposed MANOVA-Bi-LSTM | EEG | 98.13 | 97.93 | 98.16 | 98.03 |
| | SWELL | 99.80 | 99.73 | 99.78 | 99.76 |
| | WESAD | 99.50 | 99.13 | 99.41 | 99.27 |

The performance of the Bi-LSTM-based stress classification model, utilizing MANOVA for feature selection, was compared with other state-of-the-art classification models, including a Recurrent Neural Network (RNN), a Long Short-Term Memory (LSTM), a Gated Recurrent Unit (GRU), and a Bidirectional GRU (Bi-GRU), as shown in Table III. The Bi-LSTM model processes data bidirectionally, allowing it to incorporate future context, which contributes to improved classification accuracy. A key advantage of the Bi-LSTM model is its ability to efficiently process feature sequences while preserving temporal information, making it highly suitable for the precise analysis and classification of stress levels. Table IV presents a quantitative analysis of the results of the Bi-LSTM method combined with the proposed MANOVA feature selection technique for mental stress classification on the three-class WESAD dataset. Table V shows a similar analysis of the results of the proposed model on the three-class SWELL-KW dataset. The primary advantage of the Bi-LSTM model is its ability to process feature sequences efficiently while retaining temporal information, making it well-suited for accurately monitoring and classifying stress levels.

TABLE IV. PERFORMANCE ANALYSIS OF PROPOSED BI-LSTM WITH MANOVA ON THE WESAD DATASET

| Methods | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| Amusement | 97.70 | 97.71 | 99.36 | 98.53 |
| Baseline | 99.97 | 99.98 | 99.80 | 99.89 |
| Stress | 99.68 | 99.69 | 99.08 | 99.38 |
| Average | 99.50 | 99.13 | 99.41 | 99.27 |

TABLE V. PERFORMANCE ANALYSIS OF PROPOSED BI-LSTM WITH MANOVA ON THE SWELL-KW DATASET

| Methods | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| Interruption | 99.73 | 99.74 | 99.86 | 99.80 |
| No stress | 99.91 | 99.91 | 99.80 | 99.85 |
| Time pressure | 99.54 | 99.55 | 99.69 | 99.62 |
| Average | 99.80 | 99.73 | 99.78 | 99.76 |

### B. *Confusion Matrices*

Figure 3 presents the confusion matrices for the proposed Bi-LSTM model with MANOVA-based feature selection, highlighting the model's classification performance across different stress states.

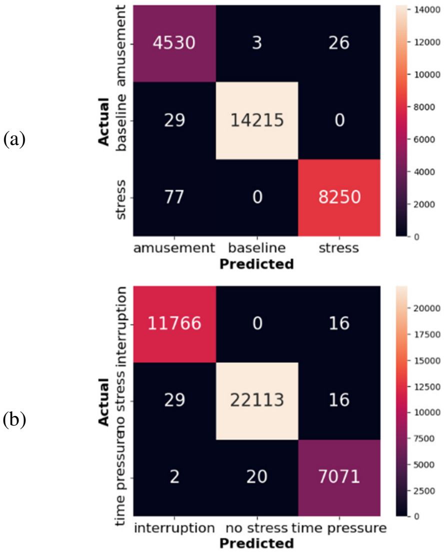

Fig. 3. Confusion matrices of the proposed MANOVA-Bi-LSTM using: (a) WESAD dataset, (b) SWELL-KW dataset.

### C. Discussion

The proposed MANOVA-Bi-LSTM model-based stress classification framework addresses the shortcomings of existing models. For precise stress level classification, the Bi-LSTM model learns the temporal data dependencies with the help of an optimal feature set selected by the proposed MANOVA technique. This feature selection and time series-based classification model achieves superior results on both the SWELL-KW and WESAD datasets compared to existing approaches that face limitations, such as misclassification, irrelevant features, and overfitting, which affect their accuracy on stress classification. ANOVA has drawbacks in feature selection, as it does not consider feature correlations, affecting the performance of stress classification. The proposed model that uses MANOVA for feature selection and Bi-LSTM for classification addresses these challenges, improving multi-class mental stress classification.

## IV. CONCLUSION

This study presented a MANOVA-Bi-LSTM model for precise feature selection and classification of individuals' stress levels. Existing classifiers face challenges in classifying stress status, as they consider irrelevant features that contain redundant information, leading to misclassification. Thus, an improved statistical technique, MANOVA, is proposed for feature ranking and efficient capture of the correlations between physiological features to identify the most informative and discriminative for mental stress classification. The Bi-LSTM model processes stress-related physiological signals, such as heart rate and skin conductance, in both forward and backward directions, effectively capturing long-term dependencies for enhanced classification. The proposed MANOVA-Bi-LSTM model achieved accuracies of 99.50% and 99.80% on the WESAD and SWELL-KW datasets, respectively, outperforming existing approaches. In the future, an advanced DL method using ECG signals can be developed to effectively enhance multi-class mental stress analysis.

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