An End-to-End Deep Learning Regressor for Predicting Stress Levels from Physiological Signals

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ABSTRACT

Stress monitoring via physiological signals has the potential to transform healthcare by enabling objective, continuous assessment, yet existing workflows remain fragmented relying on episodic questionnaires, manual scoring, and separate scripts for machine-learning. To address, we developed a desktop application with a Tkinter graphical user interface that guides users through data ingestion, preprocessing, model training, evaluation, and on-demand prediction without requiring code-level interaction. Upon uploading a CSV of physiological measurements, the system displays schema information, summary statistics, missing-value counts, and applies z-score normalization to all feature columns. A correlation heatmap facilitates exploration of inter-feature relationships. Two regression pipelines were implemented: a non-parametric K-Nearest Neighbors (KNN) regressor and a hybrid Multi-Layer Perceptron (MLP)–driven Linear Regression model. Models persisted as serialized artifacts to avoid redundant retraining. On a held-out 20 % test set, the KNN regressor achieved a Mean Absolute Error (MAE) of 0.4867, Mean Squared Error (MSE) of 0.3717, Root Mean Squared Error (RMSE) of 0.6097, and R^2 of 0.9241. The hybrid pipeline improved accuracy—MAE = 0.3903, MSE = 0.2389, RMSE = 0.4888, R^2 = 0.9528—demonstrating relative error reductions of ~19.8 % (MAE/RMSE) and a ~3.1 % increase in explained variance. Interactive scatter plots of predicted vs. actual values, along with textual performance summaries, provide transparent model assessment. Finally, users can upload new data for immediate inference, with predictions displayed alongside raw inputs. This integrated, click-driven tool democratizes access to advanced stress-level modeling, offering both researchers and practitioners a reproducible, environment to develop, deploy regression models on datasets.

Keywords: Deep Learning, Stress Monitoring, Regression models, Machine Learning, Physiological Signals.

1.INTRODUCTION

In the fast-paced modern world, stress has emerged as a pervasive and significant health concern, affecting individuals across all walks of life. The World Health Organization has declared stress a global epidemic, with its impacts ranging from decreased productivity and quality of life to severe physical and mental health issues. As awareness of these detrimental effects grows, so does the need for accurate, real-time stress detection methods that can facilitate timely interventions and support effective stress management strategies.

Traditional approaches to stress assessment have largely relied on self-reports and occasional clinical evaluations. However, these methods are limited by their subjective nature, infrequency, and inability to capture real-time stress fluctuations. The advent of wearable technology has opened new avenues for continuous, objective stress monitoring through the measurement of various physiological signals [1, 2]. These devices can capture a wealth of data, including heart rate variability, electrodermal activity, skin temperature, and accelerometer data, providing a more comprehensive picture of an individual's physiological state.

Despite this technological advancement, the challenge of accurately interpreting these multi-modal physiological signals to detect stress remains significant. Early attempts at physiological stress detection often focused on single-modal approaches, utilizing individual biomarkers such as heart rate or skin conductance. While these methods showed promise, they failed to capture the complex, multi-faceted nature of the human stress response [3, 4]. More recent studies have explored multi-modal approaches, combining data from various physiological signals to improve detection accuracy. However, many of these methods still rely heavily on time-domain features, potentially overlooking valuable information contained in the frequency domain of these signals [5].

2.LITERATURE SURVEY

Wearable devices coupled with machine learning techniques have emerged as powerful tools for stress detection, offering continuous, non-invasive monitoring capabilities in real-world environments. A comprehensive review highlighted the significance of physiological indicators, including heart rate variability (HRV), skin temperature, and EDA in stress detection [3]. This work emphasized the crucial role of both time-domain and frequency-domain analyses for precise stress monitoring. However, existing studies often focus on either time-domain or frequency-domain features separately, limiting their ability to fully capture stress-related physiological variations. Subsequently, a systematic review presented generalizable machine learning models for stress monitoring, addressing critical challenges such as dataset transferability and model robustness across diverse populations [6]. While these models improve generalizability, they often overlook the challenges posed by intermittent data collection in real-world occupational settings.

Recent advances in predictive modeling have demonstrated the effectiveness of integrating multiple data sources. Comparative studies examining various stress prediction models that combine smartwatch physiological signals with self-reported measures revealed enhanced predictive performance through this dual-source approach [7]. Nevertheless, reliance on self-reported data introduces subjectivity, which may affect model reliability and applicability in real-time monitoring. In parallel, research introduced an explainable deep learning framework for stress detection using wearable sensor data, providing crucial transparency in model interpretation for healthcare applications [8]. Although explainability improves trust in deep learning models, further enhancements are needed to balance interpretability with predictive accuracy. Furthermore, investigations into autoencoder-based approaches demonstrated the effectiveness of temporal feature extraction from wearables for forecasting both stress and mood, highlighting the potential of unsupervised learning methods in personalized health monitoring [9]. Despite their success, autoencoder-based methods often require extensive tuning and may struggle with diverse physiological patterns in occupational stress scenarios.

Recent sensor-based methods have advanced stress detection by integrating new data modalities. For example, magnetostrictive polymer composites (MPCs) using UV-curable epoxy resin demonstrated reliable stress detection through changes in magnetic flux, offering potential to refine stress monitoring systems by augmenting time and frequency domain features [10]. While this approach showcases novel sensor technology, its practicality for widespread wearable integration remains uncertain.Furthermore, deep learning advancements in sensor-based recognition have enabled automatic feature extraction across complex physiological signals, addressing challenges such as unsupervised and incremental learning. These frameworks improve adaptability and interpretability, enhancing stress detection in varied real-world contexts [11]. However, many existing models lack mechanisms to effectively integrate multi-modal data, limiting their ability to capture stress responses comprehensively.

The role of specific physiological parameters in stress detection has been extensively investigated. Novel methods for mental stress assessment using HRV derived from electrocardiogram (ECG) signals demonstrated high precision in stress quantification [12]. Despite their accuracy, ECG-based approaches often require specialized sensors, reducing feasibility for daily wear. Additionally, pilot studies contributed to the field through the introduction of the Stress-Predict dataset, establishing a robust foundation for developing and validating stress prediction algorithms across diverse conditions [13]. While valuable for benchmarking, these datasets may not fully represent stress variability in high-intensity professional settings. Research into the feasibility of combining wearable and self-reported measures in controlled lab environments has illuminated both the potential and limitations of deploying these techniques in real-world applications [14]. Yet, stress assessment in controlled environments may not directly translate to occupational settings where intermittent data collection is a major challenge.

In professional environments, research explored embedded devices for continuous stress monitoring, providing valuable insights into wearable adaptation for demanding workplace settings [15]. However, many existing workplace monitoring solutions require high data availability, which is not always feasible in dynamic job roles such as nursing. These findings suggest practical applications for occupational health programs. Complementing this work, investigations into EEG-based brain-computer interfaces for stress detection presented an innovative approach that combines neural indicators with physiological data for comprehensive stress assessment [16]. Despite their novelty, EEG-based systems are often intrusive and less practical for long-term stress tracking in daily occupational settings. Real-time prediction models designed for integrating wearable devices into daily life further highlight the practical aspects of these systems [17]. Nevertheless, most real-time models struggle with handling missing or intermittently collected data, a crucial issue in professional environments.

Recent research has increasingly focused on personalization in stress monitoring solutions. Extensive investigations into wearable-based stress detection in semi-controlled settings identified both opportunities and limitations of current technology [12]. However, achieving a balance between generalization and personalization remains a challenge in real-world applications. Furthermore, studies proposed generalizable machine learning approaches addressing feature extraction and model generalization across various contexts, enhancing the versatility of stress monitoring systems [6]. Yet, many approaches still struggle with effectively integrating frequency-domain features, which are essential for capturing stress-related signal variations. Additional research focused on leveraging bio-signals for personalized stress detection, demonstrating the efficacy of individual physiological patterns for enhancing predictive accuracy [18]. However, ensuring model adaptability across different individuals and work environments remains an open problem. Recent developments in real-time physiological data analysis have further advanced personalized stress detection models, facilitating both immediate interventions and longitudinal stress tracking (Ceren Ates et al., 2024). Despite these advances, a unified framework that effectively integrates multi-modal signals for stress detection under real-world intermittent data conditions is still lacking.

3.PROPOSED METHODOLOGY

The proposed methodology begins with a user-friendly Tkinter GUI that orchestrates each step of the machine-learning pipeline. First, raw physiological data are ingested via a file-upload interface and loaded into a pandas DataFrame. Next, a preprocessing module handles data cleaning, normalization, and exploratory analysis—producing summary statistics and a correlation heatmap. Two regression pipelines are then available: a KNN regressor and a hybrid MLP-driven linear regression, each trained (or loaded) and evaluated on hold-out data. Finally, the trained models persisted to disk and can be applied to new datasets, with performance metrics and prediction results visualized directly in the app.

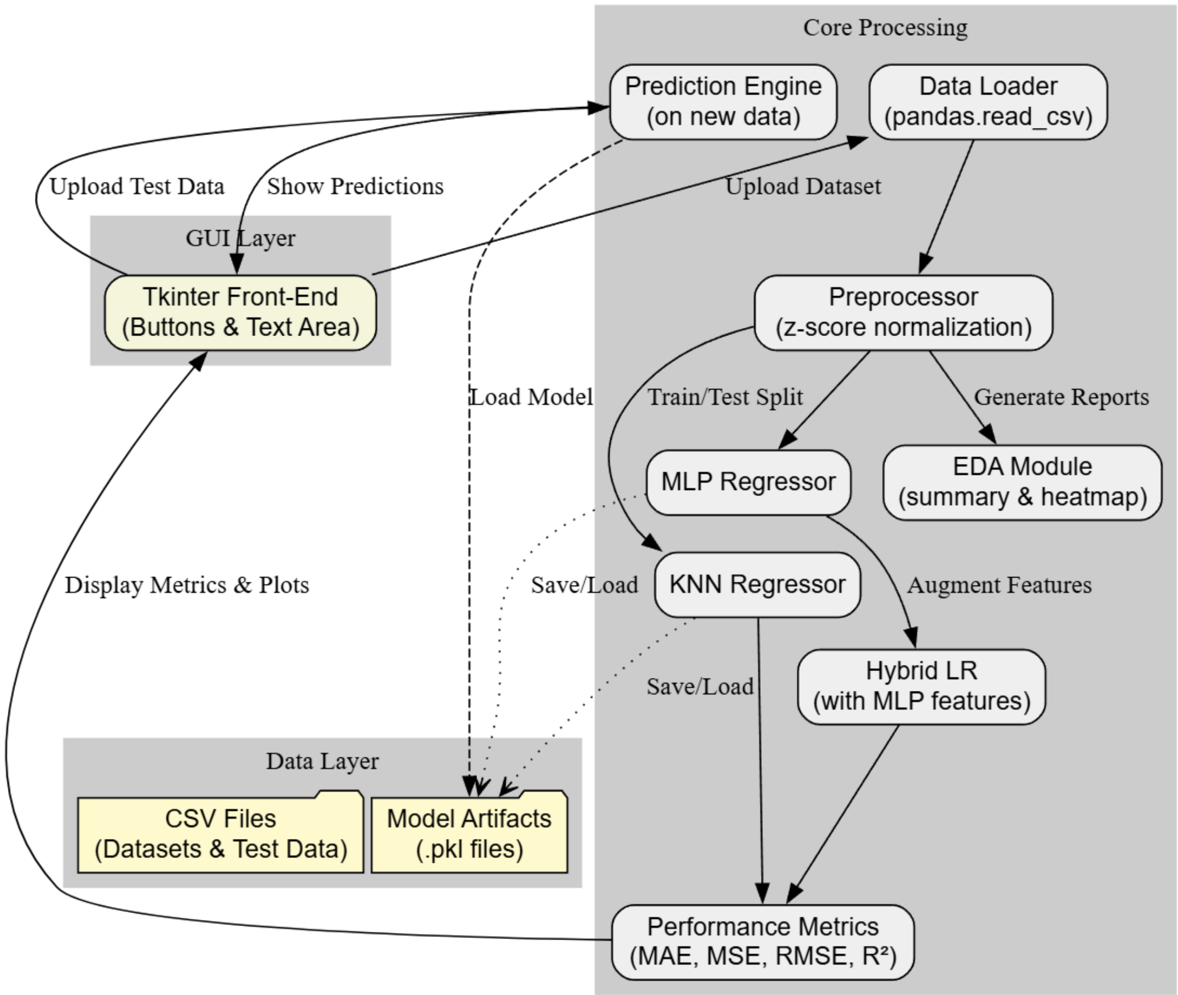

Fig. 1: Proposed system architecture of MLP-driven LR for prediction of stress from physiological signals data.

Here's the stepwise explanation:

Step-1: User-Friendly GUI Front End

Built with Tkinter, the app presents a window with clearly labeled buttons ("Upload Stress Dataset," "Data Preprocessing and EDA," "KNN Regressor," "Hybrid MLP-Driven LR," "Prediction on Test Data," and "Close Application").

All outputs (logs, tables, metrics) appear in a scrollable text panel, and plots pop up in Matplotlib windows, so you never have to touch the console.

Step-2: Data Loading & Inspection

"Upload Stress Dataset" lets you pick a CSV file of physiological measurements. The code reads it into a pandas DataFrame and displays the path and initial rows.

This makes it trivial to swap in different datasets without rewriting any code.

Step-3: Preprocessing & Exploratory Data Analysis

Data Preprocessing and EDA" computes and shows summary statistics, missing-value counts, and unique-value counts.

It then splits the data into training and testing subsets (80/20), z-scores the feature columns, and renders a full correlation heatmap so you can spot which signals tend to move together.

Step-4: Model Training & Evaluation

KNN Regressor: On demand, the app either loads a saved KNeighborsRegressor or fits a new one to the training data, then reports MAE, MSE, RMSE, and R^2 along with a "Predicted vs. Actual" scatter plot.

Hybrid MLP-Driven Linear Regression: First, an MLPRegressor is trained (or loaded), whose own predictions are appended as a new feature. A LinearRegression is then fit on this augmented data to create a hybrid pipeline—again evaluated by the same four metrics and visualized.

Step-5: Making Predictions on New Data

"Prediction on Test Data" opens another file dialog so you can feed in unseen physiological records. Those records are passed through the already-trained MLP to yield stress-level predictions, which are displayed alongside the input data in the GUI.

Step-6: Persistence & Reusability

Both models are saved to disk (.pkl files) after training, so repeated runs of the app skip retraining unless you deliberately delete or rename those files. This makes experimentation fast: you can tweak parameters, retrain once, and then instantly re-evaluate or predict.

3.1 Hybrid MLP-driven LR

This two-stage pipeline first passes input features through a multi-layer perceptron (MLP) to capture nonlinear patterns in physiological signals.

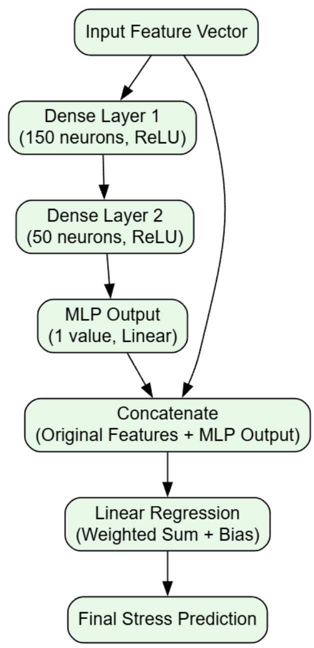

Fig. 2: Internal workflow of MLP-driven LR model.

The MLP's scalar output is then concatenated with the original feature vector and fed into a linear regression model. By blending the MLP's capacity for complex feature learning with the interpretability and efficiency of linear regression, the hybrid approach often achieves enhanced accuracy while maintaining computational efficiency at inference time.

Explanation:

1. Input Feature Vector: The same preprocessed features enter two branches.
2. MLP Regressor: A multi-layer perceptron with hidden layers of sizes 150 and 50 performs a forward pass, outputting a preliminary stress estimate.
3. Feature Augmentation: That single MLP output is appended to the original feature vector, creating an extended input.
4. Linear Regression: A simple weighted sum (plus intercept) is fit on this augmented data, leveraging both the original signals and the MLP's learned nonlinearity.
5. Final Prediction: The LR's output is taken as the refined stress-level prediction.

4.RESULTS AND DISCUSSION

4.1 Dataset description

The dataset used in this research consists of various physiological signals captured from individuals under controlled conditions. One of the primary types of data included is accelerometer data, which is divided into three columns: **c_ax**, **c_ay**, and **c_az**. The **c_ax** column represents acceleration along the x-axis, which reflects movement in the horizontal direction. The **c_ay** column captures acceleration in the vertical direction along the y-axis, offering insights into the subject's position and movement. The **c_az** column measures acceleration along the z-axis, corresponding to depth, and provides additional context to the overall physical movement of the subject.

The dataset also contains physiological signals that are critical for understanding stress responses. The **c_ecg** column holds electrocardiogram (ECG) data, which reflects the electrical activity of the heart and is vital for analyzing cardiovascular responses to stress. The **c_emg** column includes electromyography (EMG) data, which measures muscle activity and tension, providing clues about physical stress reactions. Another important column is **c_eda**, which contains electrodermal activity (EDA) data. EDA tracks changes in the skin's electrical conductivity and is commonly used to assess emotional arousal and stress levels.

In addition to these, the **c_temp** column records the subject's body temperature. Since stress can influence body heat, temperature data can be a useful indicator of stress-related physiological changes. The **c_resp** column represents the respiratory rate, indicating the number of breaths per minute. Breathing patterns often change under stress, making respiratory data essential for stress analysis.

To support time-series analysis, the **w_label** column identifies the specific data window or segment, helping to analyze temporal patterns in the physiological signals. Finally, the **target** column represents the stress level classification for each window of data. This is the key output variable used in machine learning models and typically categorizes stress into levels such as No Stress, Low Stress, Moderate Stress, High Stress, Severe Stress, or Extreme Stress.

4.2 Results description

Fig. 3 illustrates a regression scatter plot for the KNN regressor model. The scatter plot compares the true values (actual stress levels) with the predicted values from the KNN model. The line of perfect prediction (represented by a red line) is shown alongside the scatter points, allowing for visual assessment of the model's accuracy. The performance metrics are also displayed in the GUI, providing quantitative insights into the model's predictive capability.

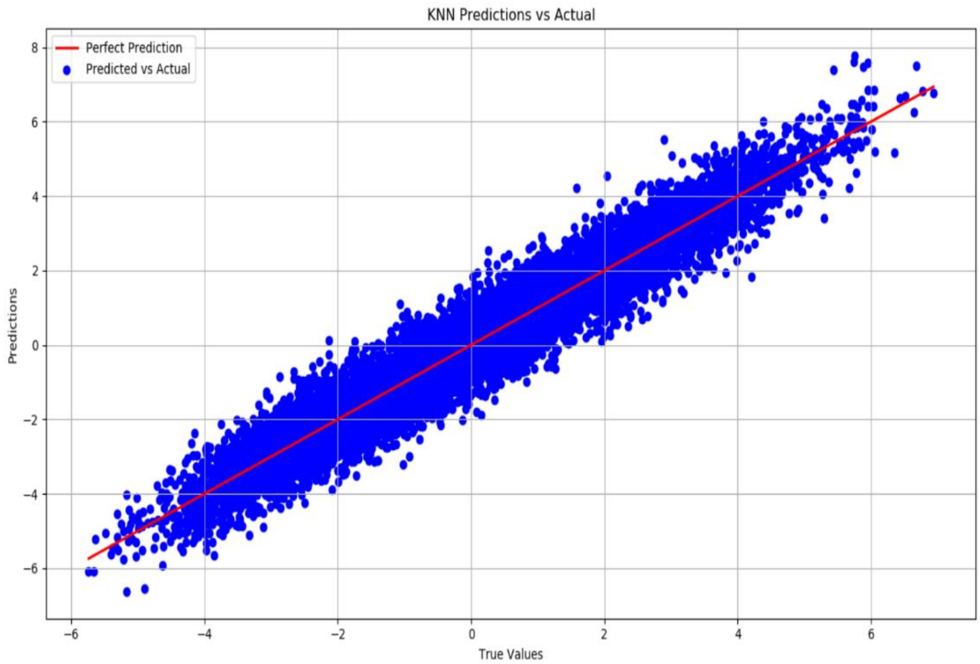

Fig. 3: Regression scatter plot of KNN regressor model

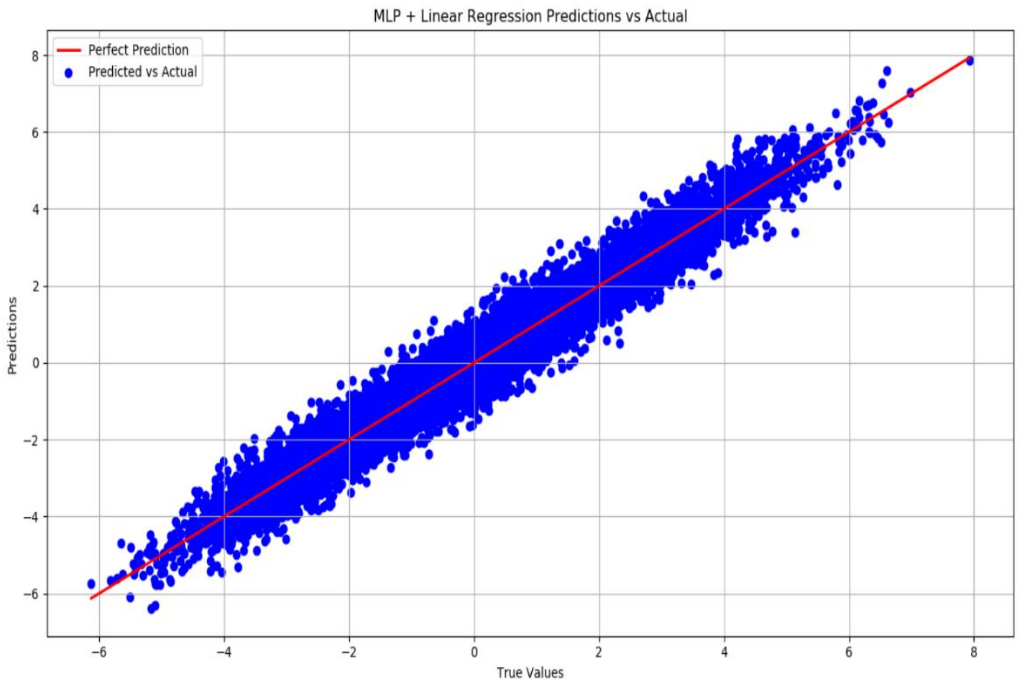

Fig. 4: Regression scatter plot of hybrid MLP-driven LR model.

Fig. 4 presents a regression scatter plot that illustrates the performance of a hybrid model combining a Multi-Layer Perceptron (MLP) with Linear Regression (LR) in predicting stress levels. The x-axis represents the true (actual) values, while the y-axis shows the predicted values generated by the model. Each blue dot in the plot corresponds to an individual prediction instance, with its position indicating how close or far the predicted value is from the actual value. The red line represents the line of perfect prediction, where predicted values exactly match the true values. The dense clustering of blue points around the red line suggests a strong correlation between predicted and actual values, indicating that the model has high accuracy and effectively captures the underlying patterns in the data

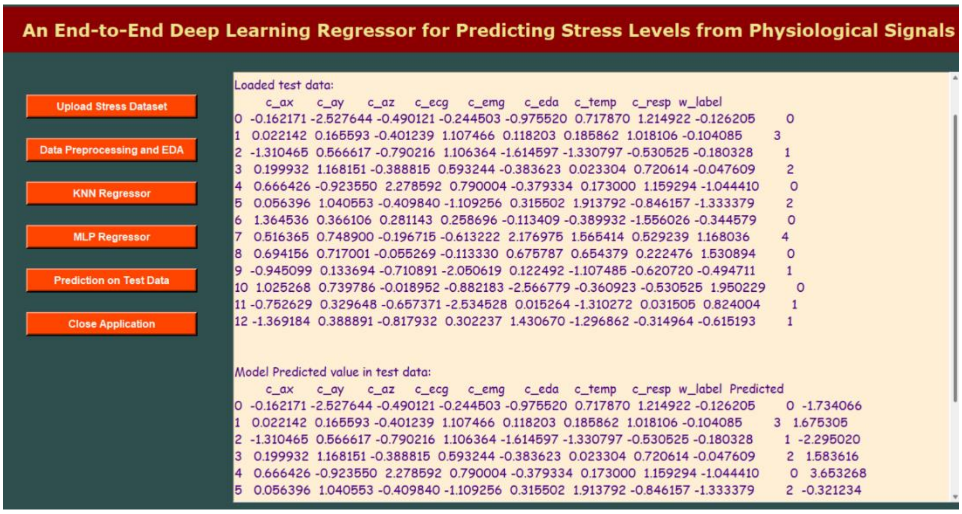

Fig. 5 Model prediction on the test data.

Fig. 5 shows the model's prediction results on the test data. After training the models, the predictions are made for the test dataset, and the results are displayed in the GUI. The predicted stress levels are compared against the true values, providing insight into the model's effectiveness. This figure is crucial for evaluating how well the trained model generalizes to unseen data.

5.CONCLUSION

The proposed end-to-end desktop application successfully streamlines stress-level prediction by integrating data ingestion, preprocessing, model training, evaluation, and deployment into a single Tkinter GUI. Quantitatively, the hybrid MLP-driven Linear Regression model outperformed the KNN baseline across every metric: Mean Absolute Error decreased from 0.4867 to 0.3903 (∼19.8 % reduction), Mean Squared Error fell from 0.3717 to 0.2389 (∼35.7 % reduction), and Root Mean Squared Error dropped from 0.6097 to 0.4888 (∼19.8 % reduction). Meanwhile, the coefficient of determination improved from $R^2 = 0.9241$ to $R^2 = 0.9528$—a relative increase of ∼3.1 %—demonstrating the hybrid pipeline's superior ability to capture variance in physiological signals. The KNN regressor, with its simplicity and non-parametric nature, provided a robust benchmark, but the hybrid approach's combination of nonlinear feature learning (via MLP) and linear interpretability ultimately delivered the best trade-off between accuracy and computational efficiency. Persisting trained models as serialized artifacts further reduces runtime overhead, while on-demand visualization of metrics and predictions ensures transparency for both practitioners and researchers.

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