Stress Detection System Based on Fuzzy and Neuro-Fuzzy Logic

Dinesh Karthik V
Electronics and Communication Engineering
Amrita Vishwa Vidyapeetham
Coimbatore, India
cb.en.u4cce23008@cb.students.amrita.edu

Mugilan S S
Electronics and Communication Engineering
Amrita Vishwa Vidyapeetham
Coimbatore, India
cb.en.u4cce23026@cb.students.amrita.edu

Dr. Vijayachandrakala K.R.M
Electrical and Electronics Engineering
Amrita Vishwa Vidyapeetham
Coimbatore, India
krm_vijaya@cb.amrita.edu

***Abstract*—Automated stress detection using physiological signals from wearable devices provides an objective and reliable alternative to subjective assessments. This study presents a comparative analysis of two soft computing approaches—Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN)—for multi-class stress classification using the WESAD dataset. Key physiological features derived from ECG, EDA, and temperature signals were preprocessed and analyzed. Experimental results show that the ANN outperformed ANFIS, achieving an overall accuracy of 85.3%, with high recall for Baseline (92.3%) and Meditation (82.9%) states, and a precision of 87.5% for Stress detection. The findings confirm the ANN's robustness for real-time stress monitoring and underline the challenges in distinguishing stress from similar arousal states.**

***Index Terms*—Stress detection, WESAD dataset, physiological signals, soft computing, Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), wearable devices, mental health monitoring.**

I. Introduction

A. Background

Psychological stress is an increasingly prevalent condition in modern society. When chronic, it serves as a significant precursor to severe health problems, including cardiovascular disease, immune system deficiencies, and mental health disorders. Traditionally, stress assessment has relied on clinical interviews and self-report questionnaires, methods that are inherently subjective, episodic, and prone to recall bias. The advent of wearable technology has revolutionized personal health monitoring by enabling the continuous and non-invasive collection of rich physiological data. Sensors embedded in smartwatches, chest straps, and other devices can capture real-time signals such as electrocardiogram (ECG), electrodermal activity (EDA), and body temperature (TEMP). These biosignals are direct manifestations of the response of the autonomic nervous system to stress, providing an objective window into an individual's psychological state and shifting the paradigm from reactive treatment to proactive healthcare.

B. Motivation

It is not easy to develop accurate stress detection systems, even with the availability of this data. The physiological response to stress exhibits high interpersonal and intrapersonal variability; the same stimulus can elicit different reactions in different people or even in the same person at different times. This inherent ambiguity and non-linearity mean that simple, threshold-based models are often insufficient, necessitating the use of advanced computational intelligence techniques.

C. Problem Definition

Therefore, the core problem addressed in this paper is the classification of psychological stress using multimodal physiological signals acquired from wearable sensors. Formulated as a supervised multi-class classification task, the goal is to design a system that can accurately distinguish between different affective states, specifically 'stress', 'meditation' and a 'neutral' baseline, using the WESAD (Wearable Stress and Affect Detection) dataset as a benchmark.

D. Objective

The principal objectives of this study are twofold: first, to develop a robust stress classification system using soft computing methodologies on the WESAD dataset, and second, to conduct a comparative performance analysis of three distinct intelligent algorithms—an Adaptive Neuro-Fuzzy Inference System (ANFIS), and a standard Artificial Neural Network (ANN).

II. Literature Survey

Stress detection has emerged as a critical research domain due to its direct implications for mental health and physiological well-being. The evolution of computational approaches—from traditional machine learning to deep learning and hybrid intelligent systems—has significantly advanced automated stress recognition using physiological, behavioral, and visual signals.

A. Physiological Signals and the WESAD Dataset

Physiological stress detection captures autonomic nervous system (ANS) responses. The WESAD (Wearable Stress and Affect Detection) dataset is a key benchmark, providing multimodal physiological data (baseline, stress, meditation) from chest (RespiBAN) and wrist (Empatica E4) sensors. While comprehensive sensor arrays (ECG, BVP, EDA, etc.) achieved 90.26% accuracy on WESAD using deep learning [4], minimalist approaches are also viable. Heart Rate Variability (HRV) is a sensitive indicator, with time-domain (SDRR, RMSSD) and frequency-domain (LF/HF) features reflecting ANS variations[2]. Electrodermal activity (EDA) is also a primary biomarker. Novel modalities like pupilometry (pupil diameter, dilation) have also shown strong potential, sometimes outperforming traditional signals [5][6].

B. Machine and Deep Learning Approaches

Classical machine learning (SVM, Random Forest) required extensive handcrafted features. Deep learning, particularly Convolutional Neural Networks (CNNs), automated this feature extraction. A CNN model [3] achieved 98% accuracy on WESAD HRV data, notably using Random Forest for feature selection to optimize performance and reduce complexity for wearable applications. However, the "black box" nature of deep learning limits interpretability, a key requirement in healthcare. This has driven research toward hybrid and fuzzy systems.

C. Fuzzy Logic Systems

Fuzzy logic addresses the inherent uncertainty and inter-individual variability of biological signals by mapping continuous data to linguistic terms. For instance, Fuzzy Support Vector Machines (FSVM) combined with Genetic Algorithm (GA) optimization have been used to select discriminative features from pupil, ECG, and PPG signals, achieving robust classification [5],[6].

D. Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) synthesizes neural network learning with fuzzy logic interpretability, using a hybrid algorithm to tune membership functions and generate data-driven fuzzy rules. ANFIS offers computational efficiency, interpretability, noise robustness, and adaptability, making it highly suitable for healthcare applications. Despite these advantages, limited research has systematically evaluated ANFIS on standardized benchmarks like WESAD, especially for wrist-only sensor data.

E. Hybrid Intelligent Systems

Recent hybrid architectures seek to balance accuracy and interpretability. One advanced system [1] combined CNN (spatial learning), BiLSTM (temporal modeling), and fuzzy inference (interpretability) to detect student stress, achieving 98.7% accuracy and outperforming baselines like SVM. While effective, such complex hybrids often require substantial computational resources, limiting their deployment on wearable devices.

This research provides a systematic comparison of neural, neuro-fuzzy, and optimized approaches on standardized data, offering guidance on balancing the trade-offs between accuracy, interpretability, and computational efficiency for practical wearable stress monitoring systems.

III. Proposed Methodology

This section details the experimental framework of our study, beginning with a description of the dataset used, followed by the data preprocessing pipeline, the feature extraction process, and the implementation details of the classification models.

A. System Overview

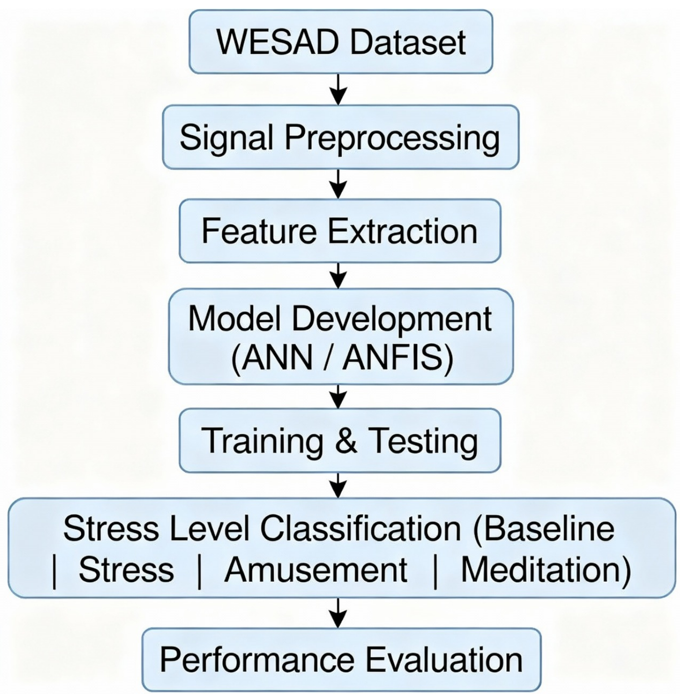

Fig. 1. Proposed Stress Detection Model

B. Dataset Description

This research utilizes the WESAD (Wearable Stress and Affect Detection) dataset, a publicly available and comprehensive resource designed specifically for research in affect recognition and stress monitoring. WESAD was created to address the lack of a standardized benchmark in the field by providing high-quality, multimodal physiological and motion data from a controlled lab study involving 15 subjects.

A key strength of the dataset is its rich sensor data, collected concurrently from two different devices: a chest-worn device (RespiBAN) and a wrist-worn device (Empatica E4). The combined data stream includes the following seven sensor modalities:

- Electrocardiogram (ECG): From the chest device, measuring the electrical activity of the heart.

- Electrodermal Activity (EDA): From both devices, the changes in skin conductance.
- Electromyogram (EMG): From the chest device, recording muscle activity.
- Blood Volume Pulse (BVP): From the wrist device, used to derive heart rate and variability.
- Respiration (RESP): From the chest device, measuring the breathing cycle.
- Body Temperature (TEMP): From both devices.
- Three-Axis Acceleration (ACC): From both devices, capture motion artifacts and activity levels.

The study created a dataset by putting people into three specific emotional states: neutral, stressed, and meditated. These states serve as the correct labels for our classification task. Our goal is to build a more detailed system that can learn to automatically tell these three states apart, rather than just detecting ”stress vs. no stress”.

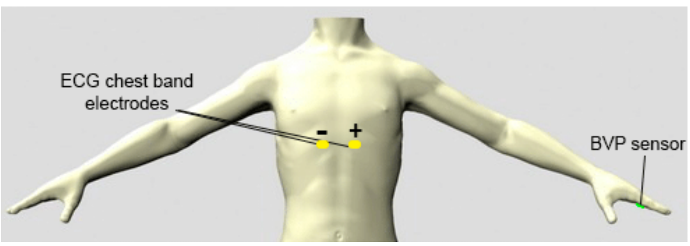

Fig. 2. Sensor Placement on Chest and Wrist for the WESAD study

C. Data Preprocessing

Raw physiological signals are susceptible to noise, motion artifacts, and baseline wander. Therefore, a preprocessing step was applied to ensure data quality and prepare the signals for feature extraction.

- Filtering: The raw signals were filtered to remove noise. For example, a band-pass filter was applied to the ECG and BVP signals to remove baseline drift and high-frequency noise.
- Normalization: All signals were normalized using min-max and z-score normalization to bring them to a common scale (between 0 and 1), preventing features with larger numeric ranges from dominating the learning process.
- Segmentation: The continuous time-series data for each subject was segmented into non-overlapping windows of 60 seconds. Each window was then treated as a single data sample for feature extraction and subsequent classification.

D. Feature Extraction

From each 60-second window of preprocessed data, a set of well-established features was extracted from each modality to create a feature vector for our models. These features were chosen to capture the key physiological changes associated with stress and arousal. The features can be categorized as follows:

- Time-Domain Features:
  - From ECG/BVP: Mean Heart Rate (HR), Standard Deviation of NN intervals (SDNN), Root Mean Square of Successive Differences (RMSSD), and the number of interval pairs with a difference greater than 50 ms (pNN50).
  - From other signals (EDA, EMG, RESP, TEMP): Mean, standard deviation, median, minimum, and maximum values.
- Frequency-Domain Features:
  - From ECG/BVP (HRV Analysis): Power in the Very Low Frequency (VLF), Low Frequency (LF), and High Frequency (HF) bands, and the crucial LF/HF ratio, which is a strong indicator of sympathovagal balance.
  - From EDA: Spectral power features from the tonic component of the signal (Skin Conductance Level).

E. Model Implementation

As per the objectives of this study, the extracted feature set was used to train and evaluate two different soft computing models: an Adaptive Neuro-Fuzzy Inference System (ANFIS), and a standard feedforward Artificial Neural Network (ANN).

The dataset was divided using a subject-independent validation scheme, where data from a subset of subjects was used for training and the remaining subjects were used for testing. The performance of each model was then evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score.

1) Adaptive Neuro-Fuzzy Inference System (ANFIS): The primary soft computing model evaluated in this study is the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is a powerful hybrid intelligent system that integrates the learning capabilities of Artificial Neural Networks (ANN) with the human-like reasoning mechanism of a Fuzzy Inference System (FIS). It was selected for this study due to its exceptional ability to model the inherent uncertainty and non-linearity of physiological signals in stress responses. While the fuzzy logic component allows the system to handle ambiguity using linguistic rules (e.g., ”IF heart rate is high AND EDA is high THEN stress is high”), the neural network component automatically tunes the parameters of these rules and membership functions from the training data.

The standard ANFIS architecture employs a five-layer feedforward network, which implements a Sugeno-type Fuzzy Inference System. The function of each layer is as follows:

- Layer 1 (Fuzzification): Each node in this layer generates membership grades for each input feature. The parameters of the nodes, which define the shape of the membership functions, are known as premise parameters.
- Layer 2 (Rule Antecedent): Each node in this layer calculates the firing strength of a fuzzy rule by multiplying the incoming membership grades.

- Layer 3 (Normalization): The firing strength of each rule is normalized by dividing it by the sum of all rules' firing strengths.
- Layer 4 (Defuzzification): The normalized firing strengths are multiplied by a first-order polynomial (the consequent of the Sugeno model). The parameters in this layer are known as consequent parameters.
- Layer 5 (Output): This single node computes the overall output as the summation of all incoming signals from the previous layer.

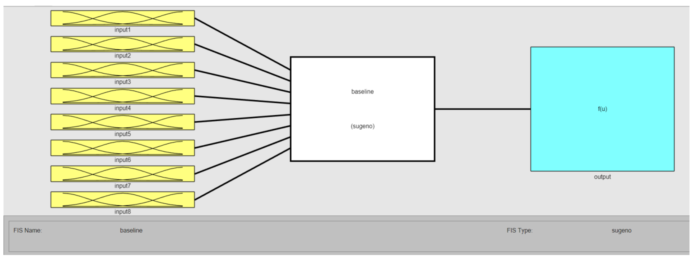

Fig. 3. Sugeno FIS Structure

For our stress classification task, a specific ANFIS configuration was implemented in MATLAB:

- Input Layer: 8 nodes, corresponding to the physiological features extracted from the WESAD dataset.
- Membership Functions (MFs): Two Generalized Bell-shaped Membership Functions (gbellmf) were used for each of the eight input variables.
- Rule Base: This configuration automatically generated a total of $2^8 = 256$ fuzzy IF-THEN rules to map the input-output space.
- Training: The network was trained using a hybrid optimization algorithm. This method combines the gradient descent algorithm to tune the premise parameters (MF shapes) and the least-squares estimation (LSE) method to determine the consequent parameters in a single forward pass, leading to faster convergence.
- Strategy: To handle the multi-class problem, a One-vs-Rest (OvR) approach was used, where a dedicated ANFIS model was trained for each affective state (e.g., 'Stress vs. Rest,' 'baseline vs. Rest,' etc.).

To ensure the model's ability to generalize, a subject-independent validation scheme was employed, where the model was trained on a subset of subjects and tested on a completely separate group of unseen subjects.

2) Artificial Neural Network (ANN): As a primary classification model, a feedforward Artificial Neural Network (ANN) was developed to serve as a robust system for stress detection. ANNs are powerful computational models adept at learning complex, non-linear patterns directly from data, making them highly suitable for classifying physiological signals. The implementation was carried out using MATLAB's Deep Learning Toolbox.

The architecture and training protocol were defined as follows:

- Feature Selection: A subset of six optimal features was selected for the model based on their strong correlation with physiological stress responses. These features are: mean chest EDA, standard deviation of chest EDA, mean wrist temperature, the LF/HF ratio from HRV, and the standard deviation of the Signal Magnitude Vector (SMV) from both chest and wrist accelerometers. All features were normalized using z-score normalization.
- Network Architecture: The network was designed as a pattern recognition network (patternnet) with three hidden layers containing 128, 64, and 32 neurons, respectively. This deeper architecture allows the model to learn hierarchical features from the data.
- Training and Optimization:
  - Algorithm: The network was trained using the Scaled Conjugate Gradient (SCG) backpropagation algorithm (trainscg), which is well-suited for large-scale problems and generally provides good generalization.
  - Data Division: The dataset was randomly partitioned into a training set (70%), a validation set (20%), and a testing set (10%).
  - Regularization: To prevent overfitting and improve generalization, L2 regularization was applied with a performance parameter of 0.2.
  - Early Stopping: An early stopping criterion was implemented to ensure the model's robustness. The training was configured to halt if the validation error failed to improve for 20 consecutive epochs, ensuring that the final model was saved at its point of optimal performance.
- Neuron Activation:

$$\boxed{y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)}$$

  where
  x_i: input features
  w_i: corresponding weights
  b: bias term
  f: activation function
- Forward Propogation:

$$\begin{aligned} \text{Hidden Layer 1:} \quad & H_1 = \text{ReLU}(W_1 X + b_1) \\ \text{Hidden Layer 2:} \quad & H_2 = \text{ReLU}(W_2 H_1 + b_2) \\ \text{Output Layer:} \quad & Y = \text{Softmax}(W_3 H_2 + b_3) \end{aligned}$$

- Loss Function: Cross Entropy

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c})$$

  where
  N: number of samples

C: number of classes
$y_{i,c}$: actual label (1 if sample i belongs to class c, 0 otherwise)
$\hat{y}_{i,c}$: predicted probability for sample i and class c

- Output Layer: The output layer consists of 4 neurons corresponding to the target classes (Baseline, Stress, Meditation), using a Softmax activation function to produce class probabilities. The model's performance was evaluated using the cross-entropy loss function.

F. Evaluation Metrics

The performance of the final ANFIS and ANN models was quantitatively assessed and compared using a set of standard, well-established classification metrics. For this multi-class problem, the metrics were calculated from the confusion matrix generated on the test set.
Accuracy: The overall percentage of correctly classified instances. It is calculated as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Confusion Matrix: A table used to visualize the performance of the classifier, providing a detailed breakdown of correct and incorrect predictions for each class (True Positives, False Positives, True Negatives, and False Negatives).
Precision: Measures the proportion of positive identifications that were actually correct. It reflects the model's exactness.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (Sensitivity):

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

IV. Results

A. Confusion Matrix

The ANN's performance, evaluated on the held-out test dataset, achieved an overall accuracy of 85.3%. The test confusion matrix provided a detailed breakdown of the model's performance for each class:

- Class 1 (Baseline): The model excelled at identifying the baseline state, demonstrating the highest recall (92.3%) and strong precision (81.4%).
- Class 2 (Stress): This was the most challenging class. While its predictions were reliable (high precision of 87.5%), it had a recall of 77.8%. This indicates the model failed to identify 22.2% of the actual stress samples, most frequently misclassifying them as the baseline state.
- Class 3 (Meditation): This class also showed robust performance with high recall (82.9%) and precision (89.5%).

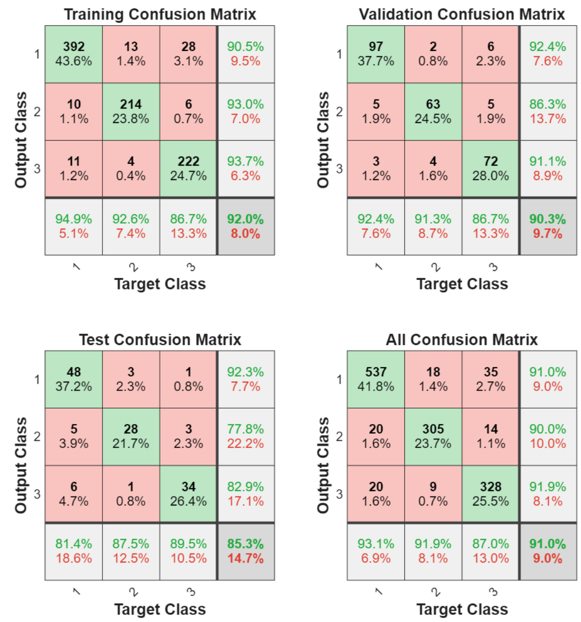

Fig. 4. Confusion Matrices for ANN Classifier

B. ROC Curve Analysis

The model's ability to discriminate between classes is further validated by the Receiver Operating Characteristic (ROC) curves, particularly the Test ROC plot.

All three class curves are positioned significantly in the top-left quadrant, far above the 45-degree line of no-discrimination. This indicates a high Area Under the Curve (AUC) and a strong classification performance for all states. The curves for Class 1 (Baseline) and Class 3 (Meditation) are nearly optimal, reflecting the excellent precision and recall values observed in the confusion matrix. The curve for Class 2 (Stress) is also robust, though slightly below the other two, visually confirming that it was the most challenging class for the model to distinguish.

C. Model Training and Convergence

The model's training progression over 200 epochs is detailed in the accompanying figures. The training process was governed by an early stopping criterion to prevent overfitting.

As shown in the training progress plot, the process was automatically terminated at epoch 200 when the "Validation Checks" - the number of consecutive epochs without an improvement in validation performance - reached the predefined patience limit of 20.

The accuracy plot illustrates why this was necessary. After an initial, rapid increase in performance, a clear divergence appears. The Training accuracy (blue line) continued to climb steadily to over 90%, indicating the model was still learning the training data. However, the Validation accuracy (red line) and Test accuracy (green dashed line) plateaued at approximately 87% and 80%, respectively. The early stopping

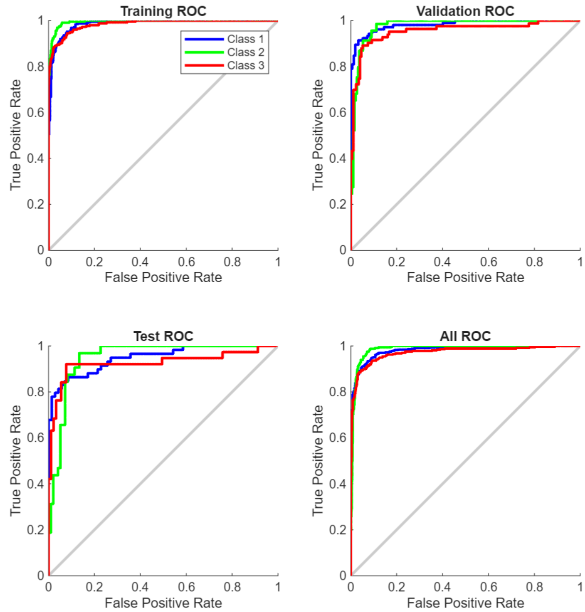

Fig. 5. ROC Curve Analysis

mechanism successfully identified this point of diminishing returns, halting the training to select the model with the best generalization performance.

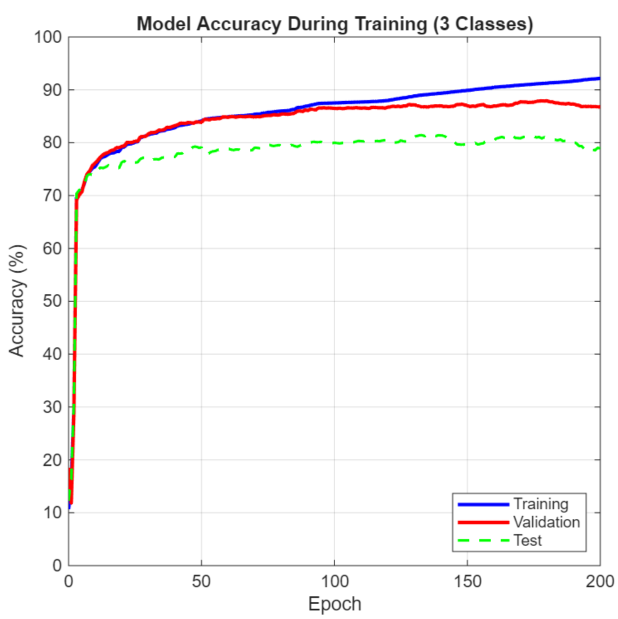

Fig. 6. Training Progress (gradient, validation checks)

D. Performance Comparison

ANFIS demonstrated superior training stability with smooth convergence (error: 0.21583) without overfitting, while ANN required early stopping at 200 epochs. The trade-off between interpretability and performance is clear: ANFIS provides transparent decision logic through fuzzy rules, whereas ANN achieves higher quantitative accuracy (85.3%) but operates as a black box. Clinical applications may prefer ANFIS for explainability, while pure prediction tasks may benefit from ANN's accuracy.

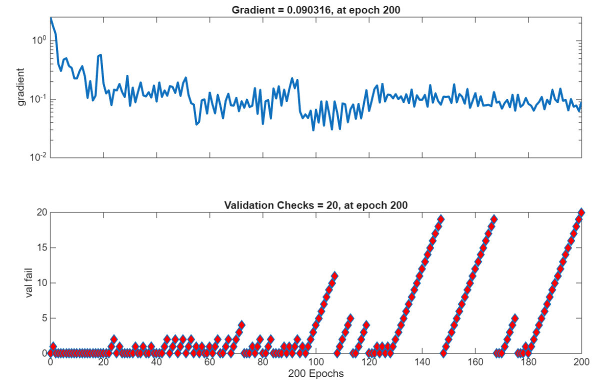

Fig. 7. Model Accuracy during Training

TABLE I
ANFIS VS. ANN MODEL CHARACTERISTICS

Feature	**ANFIS**	**ANN**
Architecture	One-vs-Rest	Multi-class
Training Stability	Good	Reasonable
Interpretability	High (Fuzzy Rules)	Low
Test Accuracy	Functional	85.3%
Epochs to Converge	50	200

REFERENCES

[1] Deepakraj, Jamuna, S. Sudhakar Reddy, Babayev Turgan Khalil, Talabaktula S. Viswanadham, M. Balamurugan, and Rajib Mandal. "Fuzzy Logic and Deep Learning Hybrid Model for Physiological Stress Detection in Higher Education." In 2025 5th International Conference on Intelligent Technologies (CONIT), pp. 1-7. IEEE, 2025.

[2] Ramteke, Ramyashri, and V. R. Thool. "Stress detection of students at academic level from heart rate variability." In 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), pp. 2154-2157. IEEE, 2017.

[3] Benita, D. Shirley, A. Shamila Ebenezer, L. Susmitha, M. S. P. Subathra, and S. Jeba Priya. "Stress detection using CNN on the WESAD dataset." In 2024 International Conference on Emerging Systems and Intelligent Computing (ESIC), pp. 308-313. IEEE, 2024.

[4] Abd Al Aleem, Mohamed, Roaa Mubarak, Nancy M. Salem, and Ibrahim Sadek. "A Deep Learning Approach Using WESAD Data for Multi-Class Classification with Wearable Sensors." In 2024 6th Novel Intelligent and Leading Emerging Sciences Conference (NILES), pp. 194-197. IEEE, 2024.

[5] Mokhayeri, Fania, and Mohammad-R. Akbarzadeh-T. "Mental stress detection based on soft computing techniques." In 2011 IEEE International Conference on Bioinformatics and Biomedicine, pp. 430-433. IEEE, 2011.

[6] Mokhayeri, F., M. R. Akbarzadeh-T, and S. Toosizadeh. "Mental stress detection using physiological signals based on soft computing techniques." In 2011 18th Iranian Conference of Biomedical Engineering (ICBME), pp. 232-237. IEEE, 2011.