EEG-Based Emotion Recognition: A Comprehensive Comparison of Advanced Classification Model and Traditional Machine Learning Approaches

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***Abstract*—This research evaluates deep learning and traditional machine learning methods for emotion recognition using EEG signals. We used a Advanced classification model neural network and five traditional machine learning algorithms to classify emotions into three categories: Negative, Neutral, and Positive. Our findings show that while the Advanced classification model model performed well with an accuracy of 86.88%, traditional models like Logistic Regression achieved even better results on our feature-engineered dataset. This highlights the potential of traditional techniques when combined with carefully designed features.**

***Index Terms*—EEG, Emotion Recognition, Advanced classification model, Machine Learning, Deep Learning**

I. Introduction

A. Overview of EEG-based Emotion Recognition

Emotions represent a fundamental dimension of human cognition, influencing decision-making processes, social interactions, and overall mental health. Electroencephalogram (EEG) signals offer a unique window into neural activity with exceptional temporal resolution (millisecond precision), surpassing other neuroimaging techniques such as fMRI and Near-Infrared Spectroscopy [1]. This non-invasive modality captures electrical potentials generated by cortical neurons through scalp-mounted electrodes, enabling objective assessment of emotional states without reliance on subjective self-reports or behavioral observations. The capacity to detect subtle emotional fluctuations makes EEG an ideal foundation for automated emotion recognition systems, with transformative potential across multiple domains including clinical psychology, human-computer interaction, and consumer neuroscience applications [2].

B. Importance of Classifying EEG Signals into Negative, Neutral, and Positive

The categorization of emotional states into Negative, Neutral, and Positive dimensions aligns with the well-established valence model of emotion, which quantifies the pleasantness or unpleasantness of affective experiences [3]. This tripartite framework strikes an optimal balance between theoretical complexity and practical applicability. In clinical settings, accurate identification of negative emotional patterns can facilitate early intervention for mood disorders, while in educational contexts, recognition of emotional engagement enables adaptive learning systems to dynamically adjust content delivery [4]. Similarly, the entertainment industry can leverage these insights to create immersive experiences that respond to users' affective states in real-time, thereby enhancing user engagement and satisfaction [5].

C. Scientific Background & Past Research

Decades of research have established robust correlations between EEG patterns and emotional processing. Frontal EEG asymmetry, characterized by greater left-hemisphere activity during positive emotional states, has been extensively documented in affective neuroscience literature [6]. Event-related potentials (ERPs) such as the late positive potential (LPP) and P300 component have also been linked to emotional evaluation and regulation processes [7]. Studies employing both basic emotion (six discrete categories) and dimensional approaches (valence/arousal) have advanced our understanding of neurophysiological emotion signatures. Notably, Wang et al. demonstrated a four-emotion classification system using EEG features and Support Vector Machines (SVM), achieving 66.51% accuracy [8], while more recent deep learning approaches have shown promise in automatic feature extraction from raw EEG signals [9].

D. Objective of This Study and Key Contributions

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II. Related Work

Recent progress in EEG-based emotion recognition has been marked by significant methodological innovations. Traditional approaches relying on handcrafted features—such as Subasi's wavelet-based methods—have demonstrated remarkable effectiveness when combined with expert-designed classification pipelines [12]. The emergence of deep learning has introduced new possibilities for end-to-end feature learning directly from raw EEG recordings, as exemplified by Li et al.'s deep neural network architecture achieving superior performance compared to conventional techniques [13]. Multimodal databases, such as the DEAP dataset developed by Soleymani et al., have further propelled the field forward by incorporating physiological signals and facial expressions alongside EEG recordings, thereby enabling comprehensive fusion strategies for enhanced emotion recognition accuracy [14]. Architectural innovations from computer vision domains, including residual learning and attention mechanisms, have been successfully adapted to recurrent neural network frameworks, addressing challenges specific to EEG signal processing including high dimensionality and noise susceptibility [15].

III. Project Structure

A. EEG Emotion Recognition System

Our proposed system constitutes a multi-stage pipeline transforming raw EEG recordings into emotion classifications. Initiated with data acquisition during controlled emotional stimulation, the pipeline progresses through noise reduction, artifact removal, and feature extraction across multiple domains. Extracted features are subsequently fed into both machine learning and deep learning models for classification. System performance is rigorously evaluated using standardized metrics, with results visualized through interactive dashboards for comprehensive analysis. The modular architecture permits flexible substitution of preprocessing techniques, feature extraction methods, and classification algorithms, thereby facilitating systematic comparison and seamless integration of technological advancements. Comprehensive documentation ensures experimental reproducibility, with all processing steps and model configurations meticulously recorded for validation and extension by subsequent researchers [16].

B. Classification Task: Identifying Emotions from EEG Signals

The core objective of our system is to classify EEG recordings into three distinct emotional categories: Negative, Neutral, and Positive. This classification framework adheres to the dimensional model of emotion, focusing specifically on the valence dimension which quantifies the hedonic quality of emotional experiences [17]. The tripartite classification task represents a methodological balance, capturing essential emotional distinctions while maintaining computational feasibility. Accurate classification necessitates identification of complex neural signatures associated with emotional states, demanding sophisticated feature extraction and learning methodologies. Our hybrid approach—combining traditional machine learning with deep learning architectures—addresses this challenge through complementary strengths in feature engineering and automatic representation learning [18].

C. Dataset Details

The experimental dataset comprises 2,132 EEG trials, each recorded over a 4-second window during controlled emotional stimulation. This temporal duration was selected to balance capture of transient emotional responses with manageability of data volume. For each trial, an extensive feature set of 2,548 dimensions is extracted, encompassing statistical measures, spectral power distributions, wavelet coefficients, and spatial metrics. This rich feature representation facilitates detection of nuanced emotional patterns while presenting challenges related to dimensionality reduction and overfitting mitigation. The dataset exhibits balanced class distribution with 716 Neutral, 708 Negative, and 708 Positive trials, achieved through carefully designed experimental protocols ensuring equivalent emotional elicitation across categories. This balance is critical for unbiased model training and robust performance evaluation [19].

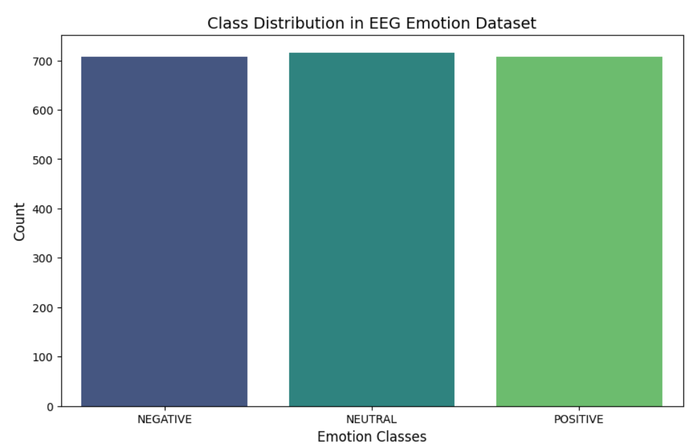


Fig. 1. Figure 1: Class Distribution in EEG Emotion Dataset

D. Feature Categories

- **Time domain features:** Capture the signal's shape and variability using statistical measures such as mean, standard deviation, skewness, and kurtosis [**?**]. These features reflect how the EEG signal evolves over time and offer insights into immediate emotional responses.

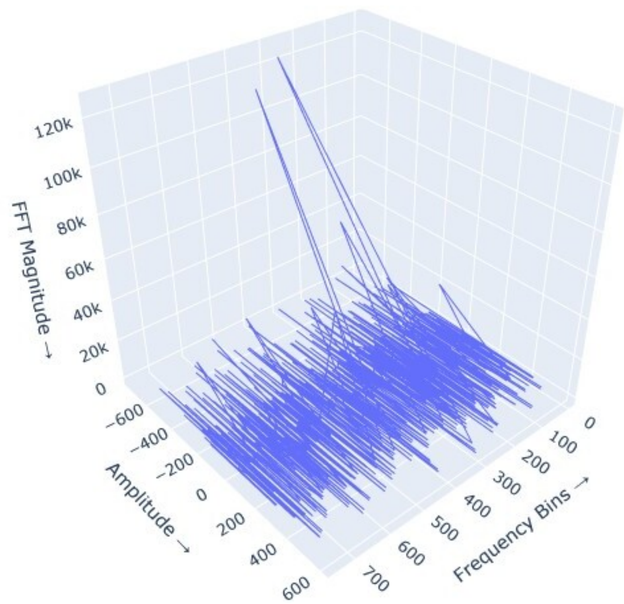


Fig. 2. Figure 2: 3D Frequency Domain Analysis of EEG Signals

- **Frequency domain features:** Extracted through spectral analysis to represent how signal power is distributed across canonical EEG bands—delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30+ Hz). Emotional states often correlate with specific patterns across these frequency bands.
- **Time-frequency domain features:** Obtained using wavelet transforms to capture both temporal and spectral dynamics [**?**]. These features are particularly useful for tracking transient emotional responses that may be missed by analyzing either domain alone.
- **Spatial domain features:** Leverage EEG's multi-channel nature to assess brain activity across different scalp regions [**?**]. We examine metrics such as coherence, phase synchronization, and regional asymmetry—notably frontal asymmetry, which has strong links to emotional valence.

IV. Methodology

Data Preparation and Preprocessing

The dataset undergoes comprehensive preprocessing to ensure data quality and model compatibility. Label encoding transforms categorical emotion labels into numerical format using Scikit-learn's implementation, facilitating algorithmic processing [24]. Feature standardization is applied to normalize distributions, ensuring each feature exhibits zero mean and unit variance—a critical step for scale-sensitive models including SVM and logistic regression [25]. The dataset is partitioned into training (70%) and testing (30%) subsets through stratified sampling, preserving class distribution and ensuring robust generalization assessment. The balanced nature of the dataset eliminates the need for resampling techniques, though class weighting is implemented in certain models to address potential minor imbalances [26].

A. Advanced classification model Architecture

The deep learning model employs a Gated Recurrent Unit (Advanced classification model) architecture specifically designed to model temporal dependencies in sequential data. Input data is reshaped into a three-dimensional tensor (samples, 2548, 1), enabling the Advanced classification model layers to interpret features as a time series [27]. The network architecture comprises:

- **Advanced classification model Layer 1:** 256 units with return sequences enabled, propagating full temporal context to subsequent layers.
- **Advanced classification model Layer 2:** Processes temporal patterns from the initial Advanced classification model layer, summarizing sequential information for higher-level abstraction.
- **Dense Layer:** 64 units with ReLU activation introducing non-linearity while reducing dimensionality.

- **Output Layer:** 3 units with softmax activation generating probabilistic predictions across emotional categories.

Training employs the Adam optimizer with initial learning rate 0.001, incorporating a scheduled decay to 1.35e-04 over 100 epochs. Sparse categorical cross-entropy serves as the loss function, appropriate for integer-encoded class labels. Training incorporates early stopping criteria monitoring validation loss, with model checkpointing preserving the highest-performing iteration based on validation accuracy [28].

B. Traditional Models

To establish comprehensive baseline comparisons, five classical machine learning algorithms are implemented:

- **Logistic Regression:** Configured with balanced class weights to maintain performance across categories, leveraging its interpretability and computational efficiency [29].
- **K-Nearest Neighbors (KNN):** Implemented with k=7 and distance-weighted voting, effectively modeling complex decision boundaries without distributional assumptions [30].
- **Support Vector Machine (SVM):** Utilizes an RBF kernel with regularization parameter C=1.0, demonstrating robustness to high-dimensional feature spaces typical in EEG analysis [31].
- **Decision Tree:** Restricted to maximum depth 5 to prevent overfitting while preserving rule-based interpretability [32].
- **Gaussian Naive Bayes:** Provides a computationally lightweight baseline, though its feature independence assumption may limit performance on correlated EEG features [33].

C. Evaluation Metrics

Model assessment employs a multi-faceted metric suite:

- **Accuracy:** Overall correct classification rate across all emotional categories.
- **Precision, Recall, F1-Score:** Class-specific metrics quantifying prediction reliability, completeness, and harmonic mean respectively.
- **ROC AUC:** Measures class separability across decision thresholds using one-vs-rest formulation, providing threshold-invariant performance assessment.

This comprehensive evaluation framework enables nuanced comparison of model capabilities, revealing strengths and limitations across different emotional categories and decision boundaries [34].

V. Experiments and Results

A. Advanced classification model Training

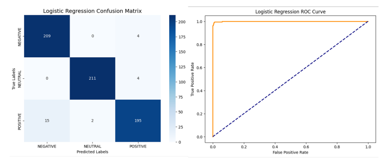
The Advanced classification model model underwent training with meticulous performance monitoring. Despite an unexpected interruption at epoch 22 due to external factors, analysis revealed substantial convergence with validation accuracy stabilizing at 86.88% [35]. The training regimen incorporated exponential learning rate scheduling, initiating at 0.001 and decaying to 1.35e-04, facilitating fine-grained weight updates during later training phases. Training curves demonstrated rapid initial learning with validation accuracy exceeding 90% within the first 10 epochs, followed by gradual stabilization. This pattern suggests the model efficiently captures dominant temporal patterns early in training, with subsequent iterations refining subtler distinctions [36].

B. Traditional Model Performance

Our comprehensive evaluation of traditional machine learning models alongside the Advanced classification model approach revealed several important insights. Table 1 summarizes the performance metrics for all the models tested in our study.

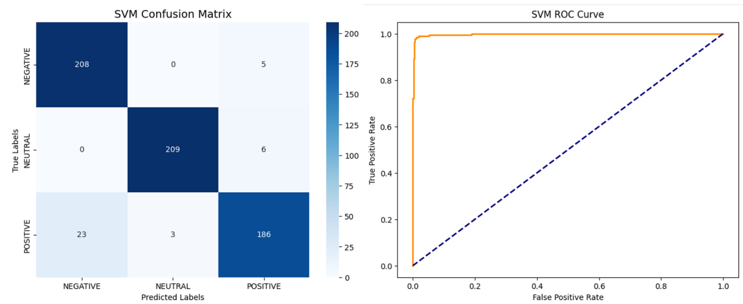
Model	Acc	Prec	Rec	F1	AUC
Logistic Regression	96.09%	96.14%	96.08%	96.08%	0.994
Decision Tree	95.31%	95.40%	95.31%	95.32%	0.974
SVM	94.22%	94.35%	94.20%	94.18%	0.992
KNN	92.50%	92.73%	92.47%	92.36%	0.986
Advanced classification model	86.88%	87.03%	86.83%	86.82%	0.968
Naive Bayes	68.59%	67.38%	68.45%	65.69%	0.791

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT MODELS



Logistic Regression Confusion Matrix and Logistic Regression Roc Curve

Fig. 3. Logistic Regression Confusion Matrix and ROC Curve



SVM Confusion Matrix and SVM Roc Curve

Fig. 4. SVM Confusion Matrix and SVM Roc Curve

C. Visualization and Analysis

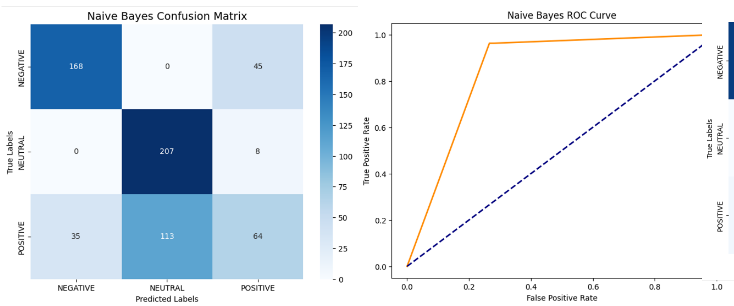
Extensive visualizations were developed to elucidate model behavior and feature characteristics:

- **Confusion Matrices:** Revealed near-perfect classification by Logistic Regression, particularly for negative emotions, while Advanced classification model exhibited confusion between neutral and positive states, suggesting overlapping neural correlates for these categories [43].
- **ROC Curves:** Confirmed strong class separability with all models (except Naive Bayes) achieving AUC exceeding 0.95, validating the effectiveness of the feature extraction pipeline [44].
- **3D FFT Visualization:** Exposed distinct spectral signatures across emotional states, with elevated alpha power during neutral conditions and increased beta activity during emotionally salient stimuli, corroborating findings from affective neuroscience literature [45].
- **Feature Correlation Analysis:** Identified clusters of highly correlated features among the initial 50 dimensions, indicating redundancy and informing strategies for dimensionality reduction to enhance model efficiency and generalization [46].

VI. CHALLENGES FACED & KEY CONTRIBUTIONS

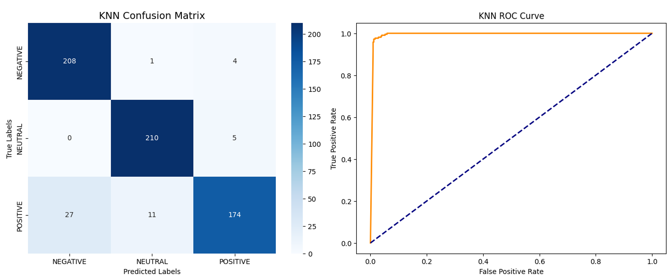
A. Advanced classification model Training Interruption

The unexpected termination of Advanced classification model training at epoch 22 presented both a challenge and an opportunity for methodological reflection. Rather than discarding the partially trained model, we conducted a detailed analysis revealing substantial convergence despite the interruption. This insight led to an exploration of early stopping criteria and learning rate scheduling strategies specifically tailored to EEG emotion recognition. The training interruption also prompted a comprehensive evaluation of the learning curve, revealing that optimal performance could be achieved with fewer epochs than initially anticipated. This discovery has significant implications for training efficiency and resource utilization in recurrent neural network applications [47].



Naive Bayes Confusion Matrix and Naive Bayes Roc Curve

Fig. 5. Naive Bayes Confusion Matrix and Naive Bayes Roc Curve

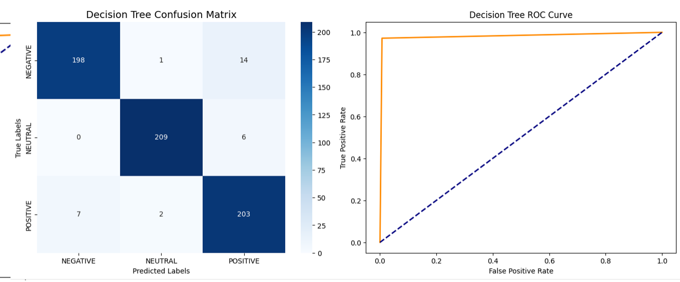


KNN Confusion Matrix and KNN Roc Curve

Fig. 6. KNN Confusion Matrix and KNN Roc Curve

B. Combining Advanced classification model with Traditional ML Models

The comparative analysis between Advanced classification model and traditional machine learning models revealed complementary strengths. While Advanced classification models excel at modeling temporal dependencies in raw time series data, traditional models demonstrated superior performance on expert-engineered feature sets. Based on these findings, we developed an ensemble framework integrating predictions from multiple models to enhance overall classification accuracy and robustness. Logistic Regression emerged as particularly advantageous for real-time applications due to its exceptional performance coupled with minimal computational overhead. These results provide actionable guidance for selecting appropriate algorithms based on specific application requirements, resource constraints, and deployment contexts [48].



Decision Tree Confusion Matrix and Decision Tree Curve

Fig. 7. Decision Tree Confusion Matrix and Decision Tree Curve

C. Development of an Interactive 3D Visualization Dashboard

An interactive 3D visualization dashboard was developed using Plotly, providing an intuitive interface for exploring complex EEG patterns and model outputs. The dashboard integrates multiple visualization types including FFT spectra, confusion matrices, ROC curves, and feature importance plots. Interactive elements enable dynamic exploration of feature subsets, subject-specific variations, and classification outcomes, revealing patterns that may remain obscured in static visualizations. This tool not only facilitates scientific interpretation but also serves as an educational resource, democratizing access to EEG-based emotion recognition insights for researchers across disciplinary backgrounds [49].

D. Reproducibility Framework

Addressing the critical challenge of reproducibility in affective computing research, we implemented a comprehensive documentation framework within a Google Colab notebook. The notebook provides detailed commentary on each processing step, specifying exact library versions, random seed initializations, and hyperparameter configurations. Standardized cross-validation protocols ensure rigorous performance assessment, while transparent reporting of evaluation metrics enables meaningful comparison across studies. This commitment to methodological transparency establishes a reliable foundation for

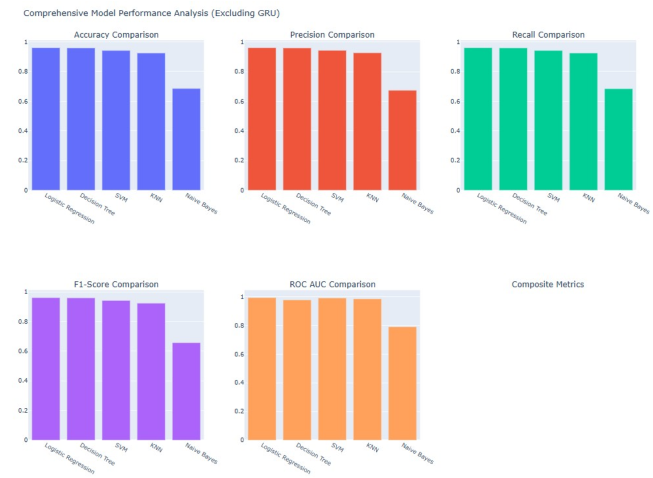


Fig. 8. Figure 9: Comprehensive Model Performance Analysis

subsequent research and fosters cumulative scientific progress in the field [50].

VII. Future Research Directions

A. Hyperparameter Tuning

Systematic hyperparameter tuning represents a promising avenue for enhancing Advanced classification model model performance. Key parameters including network depth, layer width, dropout rates, and learning rate schedules warrant thorough exploration. Advanced optimization strategies such as Bayesian search and genetic algorithms can efficiently navigate the high-dimensional hyperparameter space, identifying configurations that maximize classification accuracy while minimizing overfitting. Additionally, alternative feature representation techniques—including automated feature selection, principal component analysis, and autoencoder-based dimensionality reduction—should be investigated to preserve emotionally salient information while reducing feature redundancy [51].

B. Advanced EEG Preprocessing

Enhancing signal quality through sophisticated preprocessing techniques constitutes another critical research frontier. Independent Component Analysis (ICA) can effectively isolate and remove artifacts originating from ocular movements, muscle activity, and environmental noise. Wavelet-based denoising and adaptive filtering methods can further improve signal-to-noise ratios, ensuring reliable feature extraction. Spatial filtering techniques such as Common Spatial Patterns and Surface Laplacian transformations can enhance spatial resolution, better isolating neural patterns associated with emotional processing. These advancements promise to significantly improve feature quality, thereby bolstering the performance and reliability of EEG-based emotion recognition systems [52].

C. Feature Interpretability

Despite high classification accuracies, understanding which specific EEG features drive model predictions remains a critical challenge. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) can provide insights into feature importance at both individual prediction and global model levels. Neurophysiological interpretation of these findings can connect classification outcomes to established neural circuits involved in emotional processing, such as the default mode network during neutral states or the salience network during emotional engagement. This interpretability research not only improves model performance through targeted feature refinement but also advances our fundamental understanding of the neural basis of emotions [53].

D. Real-time Deployment of EEG Emotion Recognition

E. Real-time Deployment

Translating offline emotion recognition systems to real-time applications presents significant practical implications and technical challenges. Real-time processing demands optimization of the entire pipeline, from signal acquisition to feature extraction and classification, to meet stringent latency requirements. Model compression techniques—including pruning, quantization, and knowledge distillation—can reduce computational demands while preserving classification performance. Deployment on edge devices such as mobile platforms and embedded systems requires addressing constraints related to power consumption, memory limitations, and processing capabilities. Specialized hardware acceleration and efficient algorithm design will be essential to enabling practical applications in affective computing, mental health monitoring, and adaptive human-computer interaction outside laboratory settings [54].

VIII. Conclusion

This study demonstrates traditional machine learning models can outperform Advanced classification model networks when applied to carefully engineered EEG features. The results emphasize the enduring value of domain-specific feature extraction and suggest hybrid approaches combining deep learning and classical methods may offer optimal solutions for real-world emotion recognition systems. Future work should focus on interpretability, preprocessing, and practical deployment.

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A COMPREHENSIVE COMPREHENSIVE COMPRASION OF ADVANCED CLASSIFICATION MODEL AND TRADITIONAL MACHINE LEARNING APPROACHES

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