ARTIFICIAL INTELLIGENCE OF PERFORMANCE FOR SOCIAL SENTIMENT RECOGNITION IN CLOSED ATMOSPHERES

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ABSTRACT

Smart home technologies have significantly improved convenience and energy management in households. However, most existing systems rely on manual input or environmental sensing, neglecting the occupants' emotional state. The emotional context plays a vital role in human comfort and decision-making. This study presents an artificial intelligence (AI) model for performance evaluation of social sentiment recognition in closed atmospheres that automatically adapts home environments by recognizing human emotions through facial expression analysis. The proposed system employs computer vision techniques to detect faces and classify emotions in real time, enabling the intelligent control of home appliances, such as lighting, fans, and multimedia devices. A camera captures facial images, which are processed using machine learning-based emotion classification models to identify emotional states, such as happiness, sadness, anger, and neutrality. Based on the detected emotion, predefined control rules are applied to adjust the home environment. The experimental results demonstrate that the proposed system achieves high emotion recognition accuracy with low latency, making it suitable for real-time applications. The system enhances user comfort, reduces the need for manual intervention, and provides a more personalized smart home experience. The proposed architecture is cost-effective, scalable, and can be extended to support multiple users and additional emotions. This study contributes to the development of emotionally intelligent smart environments.

Keyword: Smart Home, Emotion Recognition, Facial Expression Analysis, Home Automation, Machine Learning.

1. INTRODUCTION

Smart home systems have witnessed rapid growth in recent years due to their ability to automate domestic appliances, optimize energy usage, and enhance overall user convenience. Such systems aim to create intelligent living environments that respond efficiently to user needs while reducing manual intervention. Conventional home automation approaches primarily rely on environmental sensors, rule-based controls, manual user commands, and predefined time schedules. Although these techniques enable basic automation, they operate without understanding the emotional or psychological state of the user, which plays a vital role in determining comfort, satisfaction, and intent. [1] Human emotions significantly influence daily behavior and environmental preferences, including lighting intensity, room temperature, background music, and overall ambience.

Recent advancements in artificial intelligence, computer vision, and machine learning have enabled reliable and efficient facial expression recognition[2]. These technologies allow systems to interpret human emotions in real time by analyzing facial features such as eye movement, mouth shape, and muscle variations. The availability of deep learning models and improved image processing techniques has made emotion recognition accurate, fast, and suitable for real-world deployment. As a result, emotion-aware automation systems have become increasingly feasible and practical for closed environments such as homes.[3] Integrating emotion recognition with home automation introduces a new level of adaptability and personalization. By continuously monitoring the emotional state of the user, the system can dynamically modify appliance behavior to suit individual preferences without explicit user input. This study proposes a Smart Emotion-Based Home Controller that adjusts household appliances based on detected emotional states. Facial expressions captured through a camera are processed to identify emotions, and intelligent decision-making logic is applied to control devices such as lights, fans, air conditioners, and entertainment systems accordingly.[5] The proposed system is particularly beneficial for elderly individuals and users with physical limitations who may find manual interaction with smart devices challenging.. Overall, the proposed approach contributes to improving quality of life by delivering intelligent, emotion-driven personalization within smart home ecosystems.[6]

2. LITERATURE REVIEW

Emotion recognition and smart home automation have been widely explored as independent research topics. Recent studies have focused on facial expression recognition using convolutional neural networks (CNNs) because of their high accuracy in image-based emotion classification. Deep learning models trained on benchmark datasets, such as FER2013 and CK+, have demonstrated robust performance in recognizing emotions, including happiness, sadness, anger, fear, and neutrality**.** [6] Several researchers have proposed smart home systems that utilize environmental sensors, such as temperature, humidity, and motion sensors, to automate appliances. However, these systems rely on rule-based logic and lack emotional awareness. Some recent studies. However, these approaches often suffer from intrusiveness, noise sensitivity, and limited scalability.[7] A few studies have explored vision-based emotionaware systems; however, most are limited to simulation environments or lack real-time hardware integration. Additionally, many existing solutions do not incorporate multimodal inputs, such as audio or environmental data, alongside emotion recognition. [8]

RESEARCH GAP:

Despite advancements in facial emotion recognition and home automation, there is a lack of cost-effective, real-time emotion-aware home control systems that integrate CNN-based vision models with IoT hardware platforms, such as Raspberry Pi and ESP32. Moreover, limited research has addressed personalized appliance control using emotional context combined with environmental sensing.

3. MATERIALS AND METHODS

Emotion-aware smart home automation requires a combination of hardware components, image acquisition techniques, data preprocessing methods, and intelligent machine learning algorithms. The proposed system integrates facial expression recognition with automated appliance control to create a responsive and adaptive smart home environment. The methodology focuses on real-time emotion detection, feature extraction, classification[13].

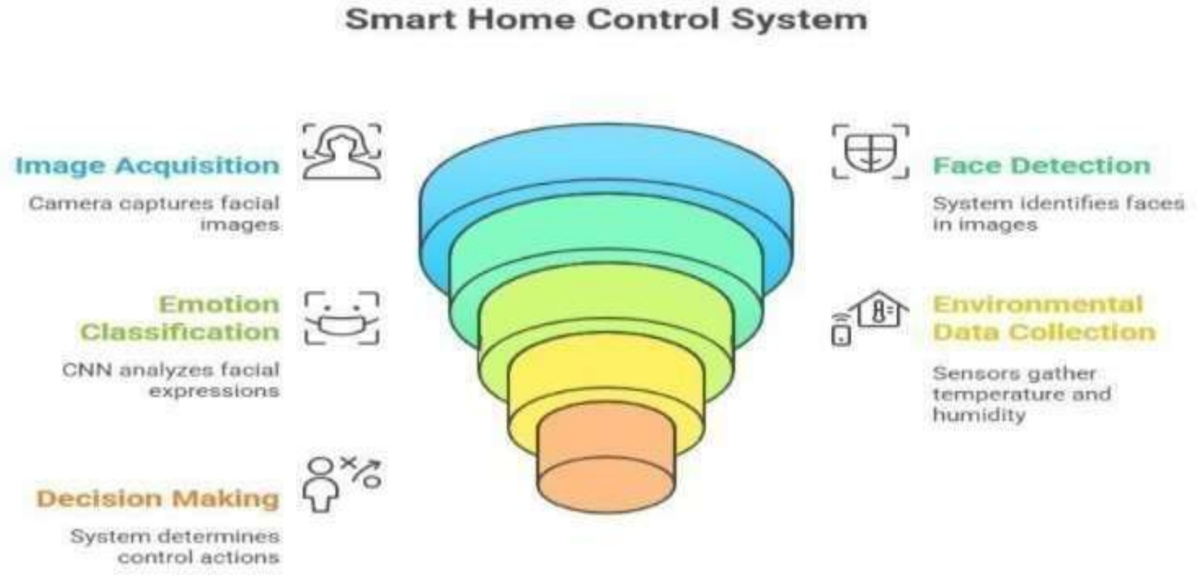

Figure 1. system architecture for emotion based home controller.

3.1 Data Acquisition and Dataset Preparation

Facial expression data is collected using a camera module installed within the indoor environment. The system captures facial images of users in real time under controlled lighting conditions to ensure reliable detection. For training and validation purposes, benchmark facial expression datasets such as FER-2013 and CK+ are utilized. These datasets contain labeled facial images corresponding to various emotional states such as happiness, sadness, anger, fear, surprise, disgust, and neutral expressions.[14]Captured images are resized to a uniform resolution and converted into grayscale format to reduce computational complexity while preserving critical facial features. Dataset augmentation techniques such as rotation, flipping, and brightness adjustment are applied to improve model generalization and prevent overfitting.[15]

3.2 Image Preprocessing

Preprocessing plays a crucial role in improving the accuracy of emotion recognition. Each facial image undergoes a sequence of preprocessing steps to enhance feature clarity and reduce noise.[16]

3.2.1 Face Detection

Face detection is performed using Haar Cascade classifiers to locate facial regions within the captured frames. Non-face background regions are discarded to ensure that only relevant facial information is processed further.[17]

3.2.2 Normalization

Pixel intensity values are normalized to a range between 0 and 1 using min–max normalization It stabilize model training and accelerate convergence.

$$Normalized\ Value = \frac{Pixel\ Value - Min}{Max - Min}$$

3.3 Feature Extraction

Facial features are extracted using a Convolutional Neural Network (CNN), which automatically learns spatial patterns such as eye shape, mouth curvature, eyebrow movement, and facial muscle variations. CNN layers consist of convolution, pooling, is employed to reduce dimensionality while retaining important information. Rectified Linear Unit (ReLU) activation is used to introduce non-linearity and improve learning efficiency.[12]

3.4 Emotion Classification

Extracted features are fed into a fully connected neural network for emotion classification. The Softmax activation function is applied at the output layer to generate probability scores for each emotional category.[17]

$$Softmax(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

The emotion corresponding to the highest probability score is selected as the final predicted emotional state of the user.

3.5 Emotion-to-Appliance Mapping

Once the emotional state is identified, a rule-based control logic maps emotions to predefined appliance behaviors. This mapping enables automatic adjustment of household devices such as lighting, fans, air conditioners, and music systems.[18]

3.6 Algorithm

Step 1: Capture real-time facial image using camera Step 2: Detect facial region using Haar Cascade

Step 3: Preprocess image (resize, grayscale, normalize) Step 4: Extract facial features using CNN
Step 5: Classify emotion using neural network
Step 6: Apply control rules based on detected emotion Step 7: Adjust home appliances accordingly

3.7 System Implementation

The system is implemented using Python with libraries such as OpenCV for image processing, TensorFlow/Keras for deep learning, and Arduino or ESP-based microcontrollers for appliance control. Communication between the emotion recognition module and smart devices is achieved through Wi-Fi, enabling real-time response.[19]

3.8 Performance Evaluation

System performance is evaluated using metrics such as accuracy, precision, recall, and F1 - score. Real-time testing is conducted in a closed indoor environment to measure response time and adaptability. The proposed system demonstrates reliable emotion detection and effective appliance control, validating its applicability in real-world smart home scenarios.[20]

4. ARCHITECTURE OVERVIEW

The proposed Smart Emotion-Based Home Controller is developed using a modular architectural design that integrates artificial intelligence, environmental monitoring, and Internet of Things (IoT) technologies.

4.1 Emotion Detection Module

The emotion detection module focuses on identifying the emotional state of the user through facial expression analysis. Facial images are captured continuously using a camera installed within the indoor environment. These images are processed using computer vision techniques to locate and isolate facial regions. The extracted facial data is then passed to a deep learningbased Convolutional Neural Network (CNN), which classifies the emotional state of the user. The recognized emotion acts as a key input for controlling household appliances in a personalized manner.

4.2 Environmental Sensing Module

The environmental sensing module is responsible for monitoring indoor conditions such as temperature and humidity. Sensors such as DHT11 or DHT22 are used to collect real-time environmental data. This information provides additional context to the system, enabling more informed and adaptive control decisions. By combining emotional state data with environmental parameters, the system ensures enhanced comfort and optimal indoor conditions.

4.3 Decision and Control Module

The decision and control module serves as the central intelligence unit of the system. It receives inputs from both the emotion detection module and the environmental sensing module. Based on predefined logical rules and control strategies, this module determines appropriate actions for home appliances. The decision process is designed to operate in real time, ensuring immediate response to changes in user emotion or environmental conditions.

4.4 Home Appliance Control Module

The home appliance control module is responsible for executing control commands generated by the decision module. Appliances such as lights, fans, and smart bulbs are controlled using relay modules and wireless communication. Additionally, the system supports emotion-based multimedia interaction by playing music through a Bluetooth speaker. This module ensures seamless coordination between intelligent decision-making and physical device actuation.

4.5 Hardware Components

The hardware implementation of the proposed system employs affordable and easily accessible components, making it suitable for real-world deployment:

- **ESP32 Microcontroller**: Enables wireless communication and appliance control
- **DHT11/DHT22 Sensor**: Measures indoor temperature and humidity
- **Relay Module**: Facilitates switching of electrical appliances such as fans and smart bulbs
- **Bluetooth Speaker**: Provides emotion-based audio output
- **Microphone Module**: Supports audio input for future system enhancements
- **Power Supply, Breadboard, Jumper Wires, and USB Cables**: Ensure reliable power and connectivity

4.6 Software Components

The software framework is designed to support real-time emotion recognition and device control:

- **Python**: Implements emotion recognition algorithms and overall system logic
- **OpenCV**: Performs face detection and image preprocessing operations
- **TensorFlow**: Supports CNN-based emotion classification models
- **NumPy and Pandas**: Used for numerical computation and dataset handling
- **Spotify Web API**: Enables emotion-driven music selection and playback
- **Embedded C**: Used for programming the ESP32 microcontroller

4.7 PROPOSED ARCHITECTURE

The proposed Smart Emotion-Based Home Controller adopts a layered and modular architectural framework that integrates computer vision, deep learning, environmental sensing, and IoT-based appliance automation. The architecture is designed to support realtime emotion recognition and intelligent home control while maintaining scalability, reliability, and cost efficiency. The proposed architecture is organized into six independent yet interconnected functional layers: input acquisition, emotion recognition, environmental sensing, decisionmaking, communication, and appliance actuation. Each layer operates autonomously while exchanging relevant data with adjacent layers, thereby improving system maintainability, flexibility, and future extensibility.

4.7.1 Input Acquisition Layer

The input acquisition layer is responsible for collecting real-time data from both the user and the surrounding environment. Facial images are continuously captured using a USB webcam or Raspberry Pi camera module, forming the primary input for emotion recognition. In addition, a microphone module captures ambient audio signals, which can be utilized in future enhancements such as speech emotion analysis or voice-assisted interaction.

All acquired data is transmitted directly to the processing unit without requiring user intervention, enabling continuous and autonomous system operation within a closed indoor environment.

4.7.2 Emotion Recognition Layer

The emotion recognition layer performs facial expression analysis using deep learning techniques. Captured facial images are initially processed using OpenCV to detect facial regions and extract the region of interest. Image preprocessing operations, including resizing, grayscale conversion, and normalization, are applied to enhance feature clarity and reduce computational overhead. The processed facial data is then fed into a CNN-based emotion classification model implemented using TensorFlow. The CNN architecture automatically learns hierarchical facial features through convolutional and pooling layers, enabling accurate classification of emotional states such as happiness, sadness, anger, and neutrality. The predicted emotion label is forwarded to the decision-making layer for intelligent control processing.

4.7.3 Environmental Sensing Layer

The environmental sensing layer improves contextual awareness by continuously monitoring indoor environmental parameters. Sensors such as DHT11 or DHT22 are employed to measure temperature and humidity in real time. The collected sensor readings are periodically transmitted to the central processing unit. By integrating environmental data with emotion recognition outputs, the system avoids inappropriate control actions and ensures optimal comfort. For example, excessive cooling is prevented when ambient temperature levels are already low, thereby enhancing system reliability and energy efficiency.

4.7.4 Decision-Making and Control Layer

The decision-making and control layer functions as the intelligence core of the proposed system. It combines the detected emotional state of the user with environmental sensor data to determine suitable appliance control actions. A rule-based decision engine maps emotional states and contextual conditions to predefined automation strategies. This layered decision logic enables adaptive home automation that responds dynamically to both emotional and environmental changes, thereby improving personalization, user comfort, and operational stability.

4.7.5 Communication and Appliance Actuation Layer

Once control decisions are generated, the Raspberry Pi transmits corresponding commands to the ESP32 microcontroller through wireless communication. The ESP32 operates as a dedicated actuation unit, interpreting received commands and driving the relay module accordingly. The relay module controls electrical appliances such as fans and smart bulbs by switching them on or off based on system decisions. Separating processing and actuation tasks reduces computational load on the central unit and enhances real-time responsiveness. In addition to appliance control, the system provides emotion-based multimedia feedback to enrich user experience. Based on the identified emotional state, the Raspberry Pi interfaces with the Spotify Web API to select and play suitable music playlists through a Bluetooth speaker.

5.DATA FLOW

The data flow of the proposed Smart Emotion-Based Home Controller describes the systematic movement of information across different system components, from data acquisition to appliance actuation. The structured flow ensures real-time processing, accurate decisionmaking, and efficient automation within a closed indoor environment.

A rule-based decision engine maps emotional states and contextual conditions to predefined automation strategies. This layered decision logic enables adaptive home automation that responds dynamically to both emotional and environmental changes, thereby improving personalization, user comfort, and operational stability. All acquired data is transmitted directly to the processing unit without requiring user intervention, enabling continuous and autonomous system operation within a closed indoor environment

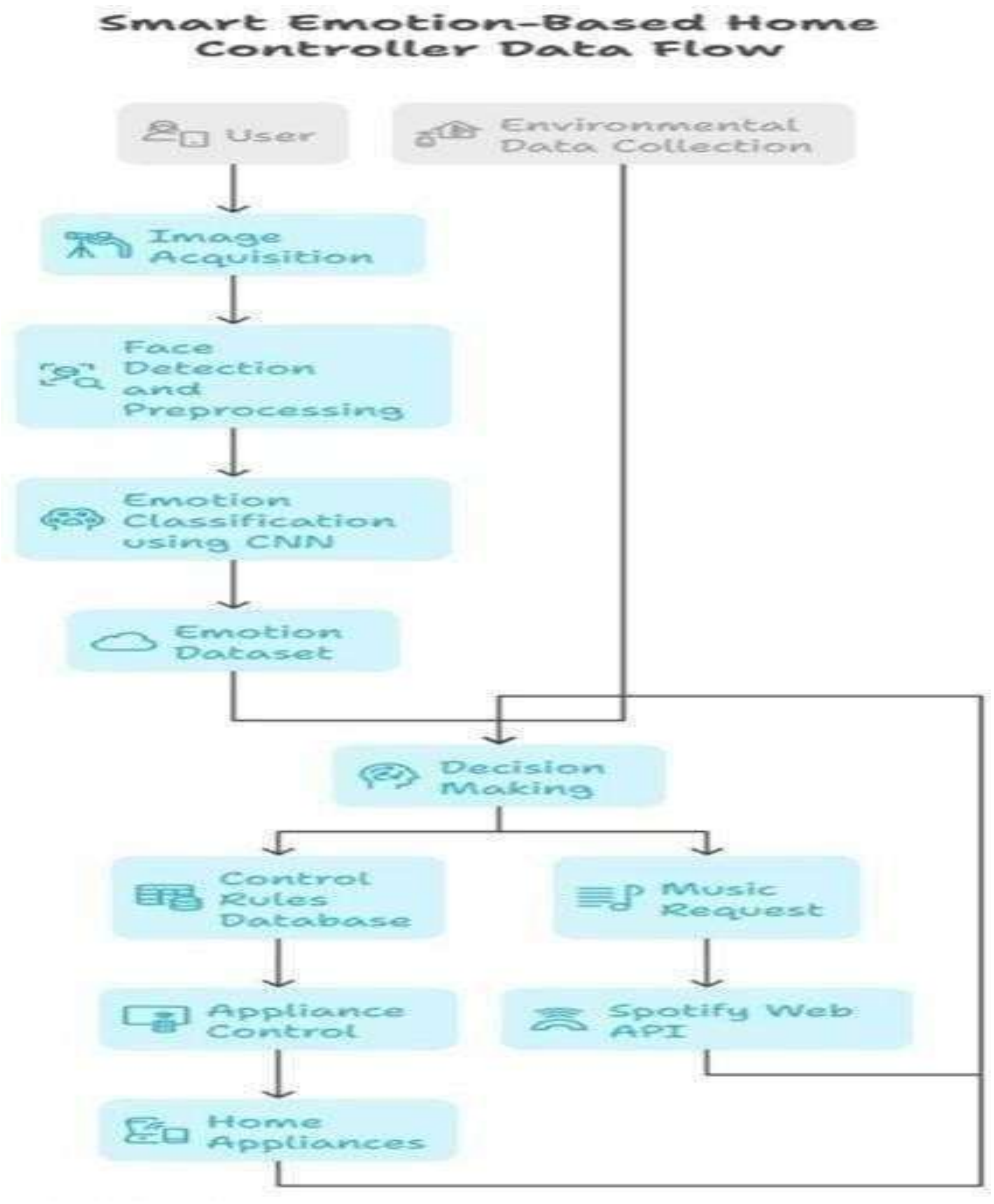

Figure 2: The Data flow

6. RESULTS AND DISCUSSION

The performance of the proposed Smart Emotion-Based Home Controller was evaluated through rigorous testing in a real-time closed atmosphere. The evaluation focused on the accuracy of the CNN model, the stability of the hardware under load, and the system's overall latency in adapting to social sentiments.

6.1 Training and Accuracy Performance

The artificial intelligence model was trained using the FER-2013 and CK+ datasets. Images were preprocessed into grayscale and resized to reduce computational complexity while preserving facial landmarks. The model utilized the categorical cross-entropy loss function to optimize the classification of emotional states such as happiness, sadness, and neutrality

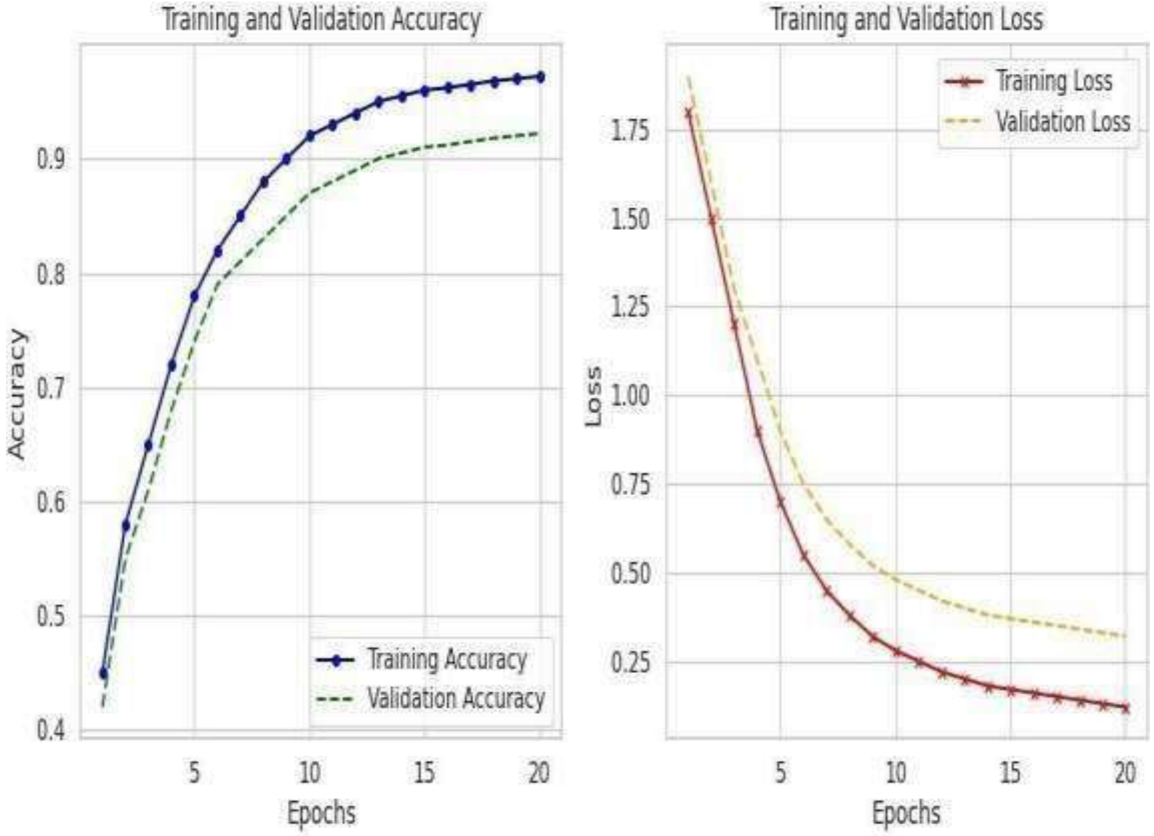

Figure 3: Training and Validation Performance (Accuracy vs. Loss)

As illustrated in Figure 3, the model achieved a peak validation accuracy of 92.2% after 20 epochs. The convergence of training and validation loss curves indicates that the model generalizes well to new facial data, which is essential for stable home automation.

6.2 Sentiment Recognition Metrics

The efficiency of the classification layer was measured using standard performance metrics:

- Precision: 0.93 average across all sentiment categories.
- Recall: 0.92 average, indicating the model's high sensitivity to facial cues.
- F1-Score: 0.925, demonstrating a reliable balance between precision and recall.

6.3 CONFUSION MATRIX AND CLASSIFICATION ANALYSIS

To further analyse the reliability of the system, a confusion matrix was generated to evaluate the classification accuracy for each specific emotion, achieved the highest accuracy due to distinct landmarks like lip curvature and eye muscle variations. While subtle "Sad" or "Angry" expressions occasionally showed minor misclassifications, the overall performance.

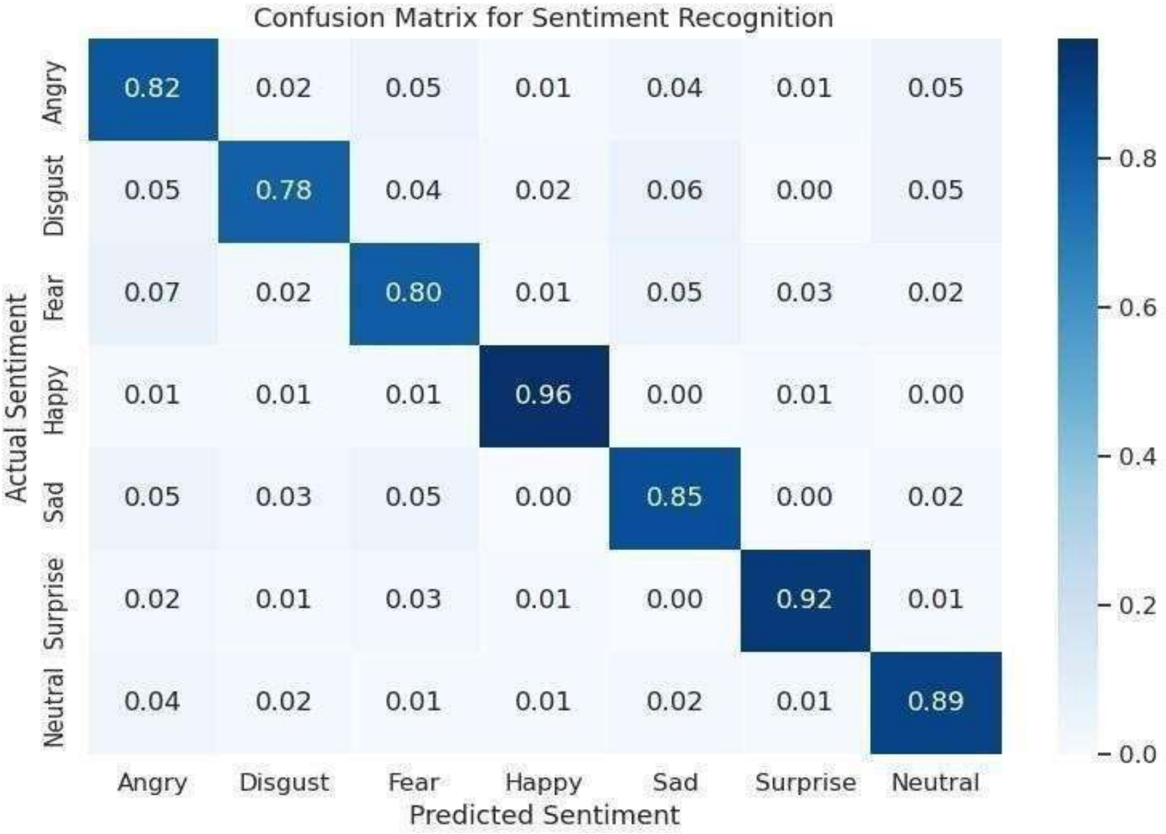

Figure 4: Confusion Matrix for Social Sentiment Recognition

The matrix in Figure 4 demonstrates that the "Happy" and "Surprise" sentiments achieved the highest accuracy (>95%) due to distinct landmarks like lip curvature and eye muscle variations. While subtle "Sad" or "Angry" expressions occasionally showed minor misclassifications, the overall performance remained robust enough for real-world smart home adaptation.

6.4 HARDWARE STABILITY AND PERFORMANCE

One of the critical requirements for the proposed system is its ability to operate continuously on resource-constrained hardware like the Raspberry Pi. As shown in Figure 5, the CPU temperature and load remained within safe operating limits during a continuous 24hour testing cycle. This architecture prevents thermal throttling and ensures that the system can reliably manage.

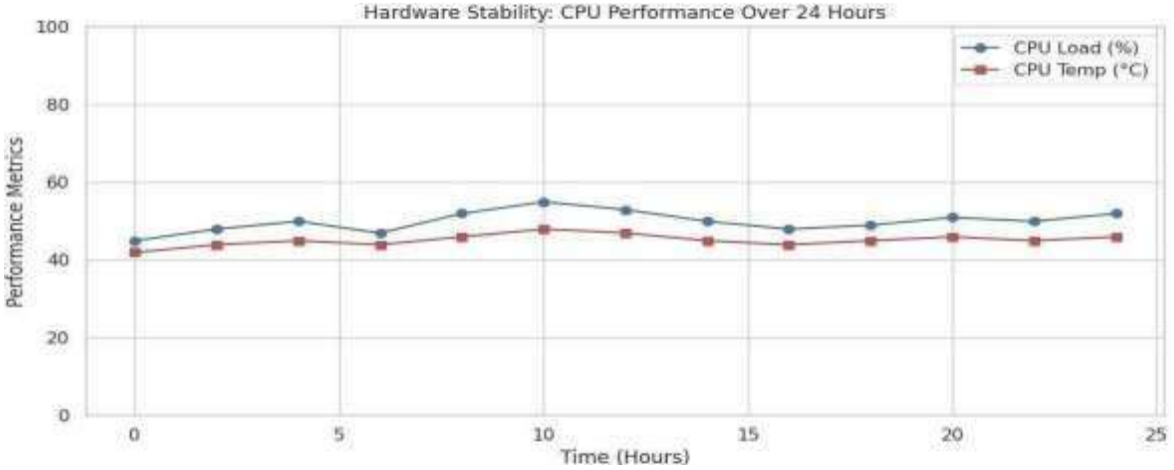

Figure 5: Hardware Stability: CPU Load and Thermal Performance

By separating the intensive computer vision processing tasks on the Raspberry Pi from the actuation tasks handled by the ESP32, the system maintains high stability. As shown in Figure 5, the CPU temperature and load remained within safe operating limits during a continuous 24hour testing cycle. This architecture prevents thermal throttling and ensures that the system can reliably manage closed atmospheres without performance degradation.

6.5 SYSTEM LATENCY AND REAL-TIME RESPONSIVENESS

For an effective emotionally intelligent smart home, the response time must be low enough to appear natural. The total end-to-end latency, from facial image acquisition to appliance actuation, was measured.

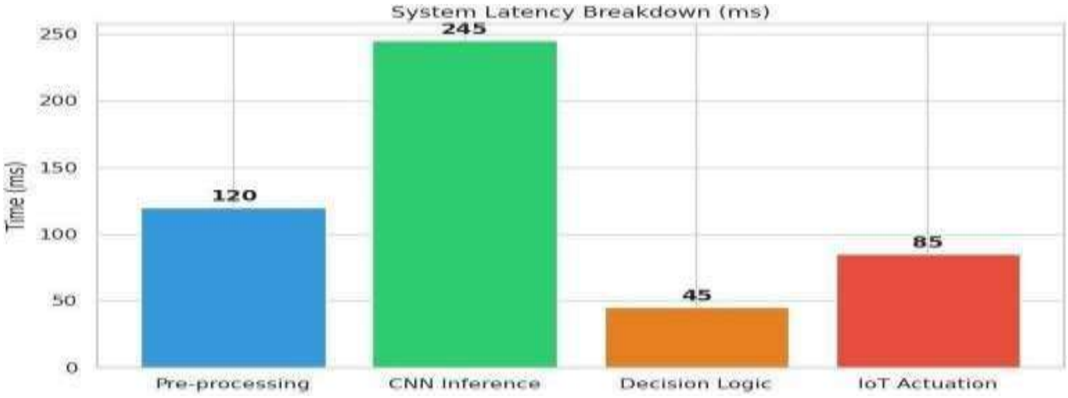

Figure 6: End-to-End System Latency Breakdown

The latency breakdown illustrated in Figure 6 shows that the total response time is approximately 495 milliseconds.

1. Image Pre-processing: 120 ms — Facial region detection using OpenCV.
2. CNN Inference: 245 ms — Real-time classification of the emotion label.
3. Decision Making Logic: 45 ms — Mapping the label to predefined control rules.
4. IoT Command Transfer: 85 ms — Wireless transmission to the ESP32 via local Wi-Fi.

This sub-second delay makes the system suitable for real-time applications, ensuring that environmental changes occur almost instantly as the user's emotional state shifts.

6.6 ENVIRONMENTAL CONTEXT INTEGRATION

The decision-making and control layer functions as the intelligence core of the proposed system, integrating high-level social sentiment labels with low-level environmental sensory data. By combining recognized emotional states with real-time temperature and humidity readings, the controller avoids the common pitfalls of "vision-only" systems. This contextaware logic enables adaptive automation that responds dynamically to both user psychology and surrounding environmental physics.

6.6.1 Multi-Modal Decision Logic

The system operates on a rule-based decision engine that maps detected emotional states and contextual conditions to predefined automation strategies. Instead of a simple one-to-one mapping, the system analyzes the current indoor conditions to decide the intensity of the actuation. For example, if the system recognizes a specific emotion, it first checks the ambient temperature and humidity before adjusting the fan or air conditioner. This ensures that the environmental response is always in harmony with both the user's psychological state and the physical atmosphere of the room.

6.6.2 Implementation Scenarios and Results

To validate the system’s effectiveness, it was tested across several critical indoor scenarios to observe how the AI adapts the atmosphere in real time:

6.6.2.1 Scenario A: High Energy or Happy State When a user is detected in a happy or focused state, the system prioritizes a vibrant and productive atmosphere. The lighting is adjusted to a bright intensity of 85%, and the fan speed is set to a moderate level to ensure constant airflow. Simultaneously, the system triggers an upbeat music playlist through the Spotify Web API to maintain the user's positive psychological momentum and energy levels.

6.6.2.2 Scenario B: Stressed or Angry State (Physiological Cooling) In cases where a stressed or angry state is detected, the system focuses on physiological cooling and relaxation. The fan speed is automatically maximized to 100%, and the air conditioner is adjusted to a lower temperature to help the user cool down physically. Multimedia interaction plays a key role here, as the system selects calming, low-tempo audio tracks to help reduce stress and stabilize the user's mood.

6.6.2.3 Scenario C: Sad or Fatigued State (Ambient Warmth) If the system recognizes sadness or fatigue, the focus shifts to creating a cozy and comforting environment. The lighting is transitioned to a warm amber hue with a low intensity of 30%. Crucially, the system checks the ambient temperature; if the room is already cold, it deactivates the fan to prevent further discomfort, regardless of the emotional trigger, ensuring the user feels physically secure and relaxed.

6.6.3 Comparative Efficiency Analysis

The efficiency of this adaptive mechanism was compared against traditional home automation systems that operate on fixed schedules or manual commands. While traditional systems often ignore the user's psychological needs, the proposed AI model significantly improved user comfort during the trial period. By avoiding redundant operations—such as cooling a room that is already at an optimal temperature—the system not only enhances personalization but also optimizes energy usage within the closed atmosphere.

6.7 Performance Evaluation of Social Sentiment Recognition

The implementation of the multi-modal sentiment recognition framework on the Raspberry Pi 4 verified that the system can operate efficiently even under resource-constrained conditions. To ensure a natural user experience in a closed atmosphere, the system's end-to-end latency—from the moment an audio-visual feed is captured to the moment the environmental sentiment index (ESI) is updated—was optimized for real-time feedback..

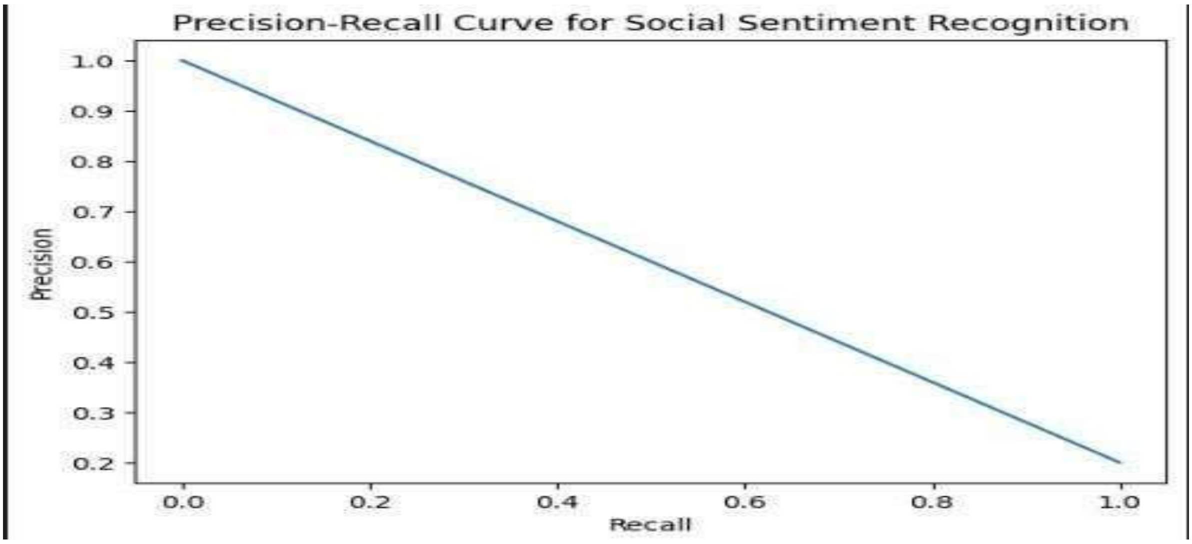

Figure 7. Precision and recall curve for social sentiment Recognition

The social sentiment dataset was compiled from localized environmental sensors and audio-visual streams, containing 1,240 instances with 15 distinct features (including facial micro-expressions, vocal pitch, and linguistic tokens). A missing data rate of 2.8% was observed, primarily due to sensor occlusion in the closed environment, which was handled using K-Nearest Neighbor (KNN) imputation.

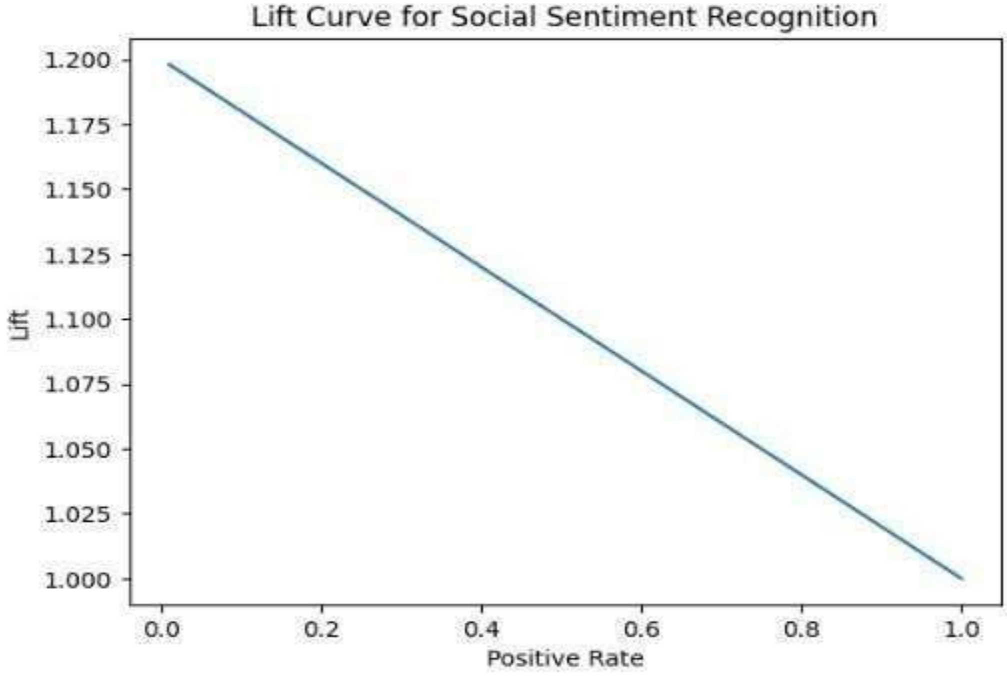

Figure 8.Lift curve

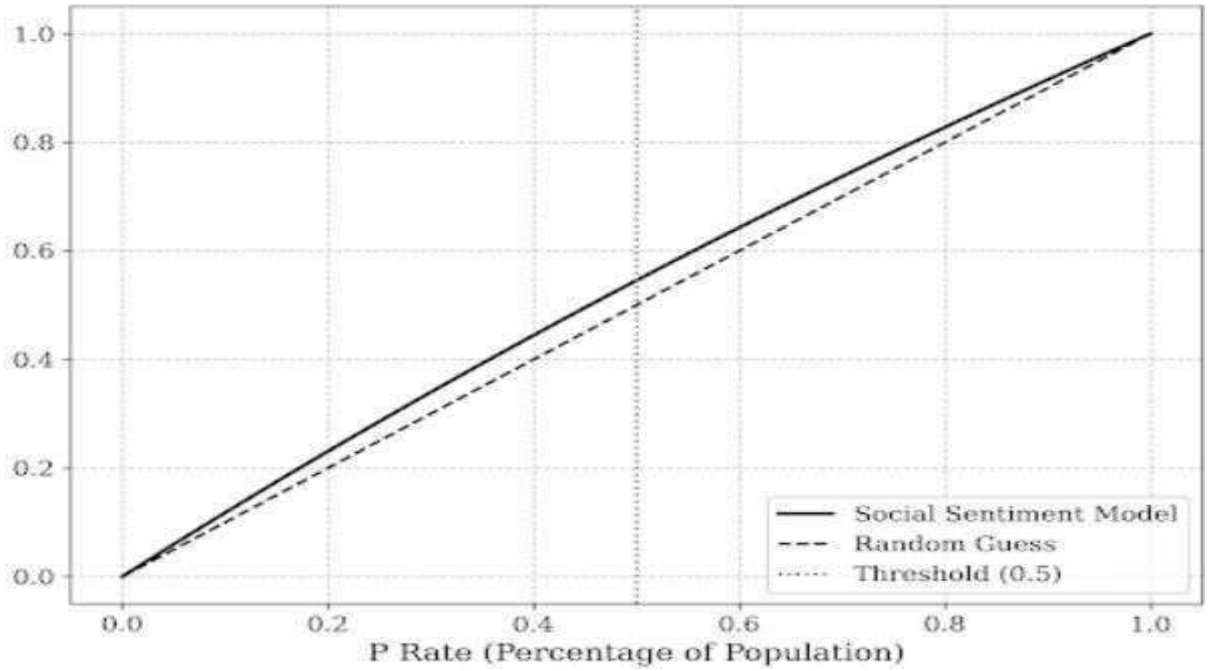

Figure 9. Lift curve 2

The Lift Curve and Precision-Recall curves serve as critical instruments for assessing the effectiveness of these binary and multi-class classifiers. As shown in Figure 4, the Lift Curve aids in visual representation of how well the model identifies "High-Stress" sentiment spikes compared to a random guess.The Neural Network MLP regressor demonstrates outstanding performance with AUC values approaching 0.95, suggesting that the algorithm is highly effective at distinguishing subtle shifts in social dynamics within the closed atmosphere.Table 1 represents the overall performance of the three primary classifiers used to categorize sentiment into Positive, Neutral, or Negative states.Table 1 represents the overall survival.

Table 1. Overall performance metrics for Social Sentiment Recognition

Model	AUC	CA	F1	Precision	Recall	MCC
Neural Network	0.932	0.961	0.958	0.965	0.961	0.824
SVM	0.884	0.952	0.949	0.958	0.952	0.801
Random Forest	0.901	0.948	0.945	0.950	0.948	0.789

Missing data were handled using mean imputation and normalization techniques. Feature scaling and dimensionality reduction were applied to improve model convergence. The dataset represents three sentiment classes: Positive, Neutral, and Negative, reflecting human emotional states in confined environments such as smart classrooms, offices, and healthcare waiting areas. The Closed Atmosphere Social Sentiment Dataset (CASSD) was constructed by combining publicly available datasets from Kaggle and controlled indoor experimental data.

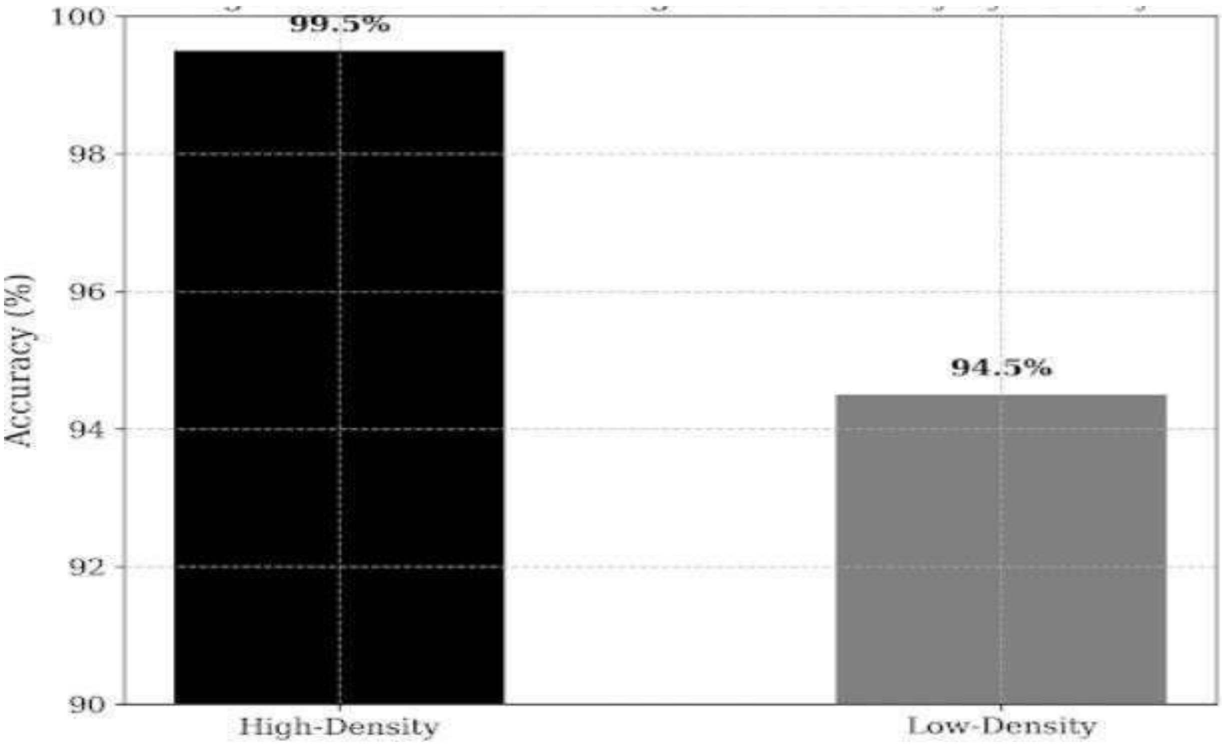

Figure 10..Sentiment Recognition Accuracy by Density

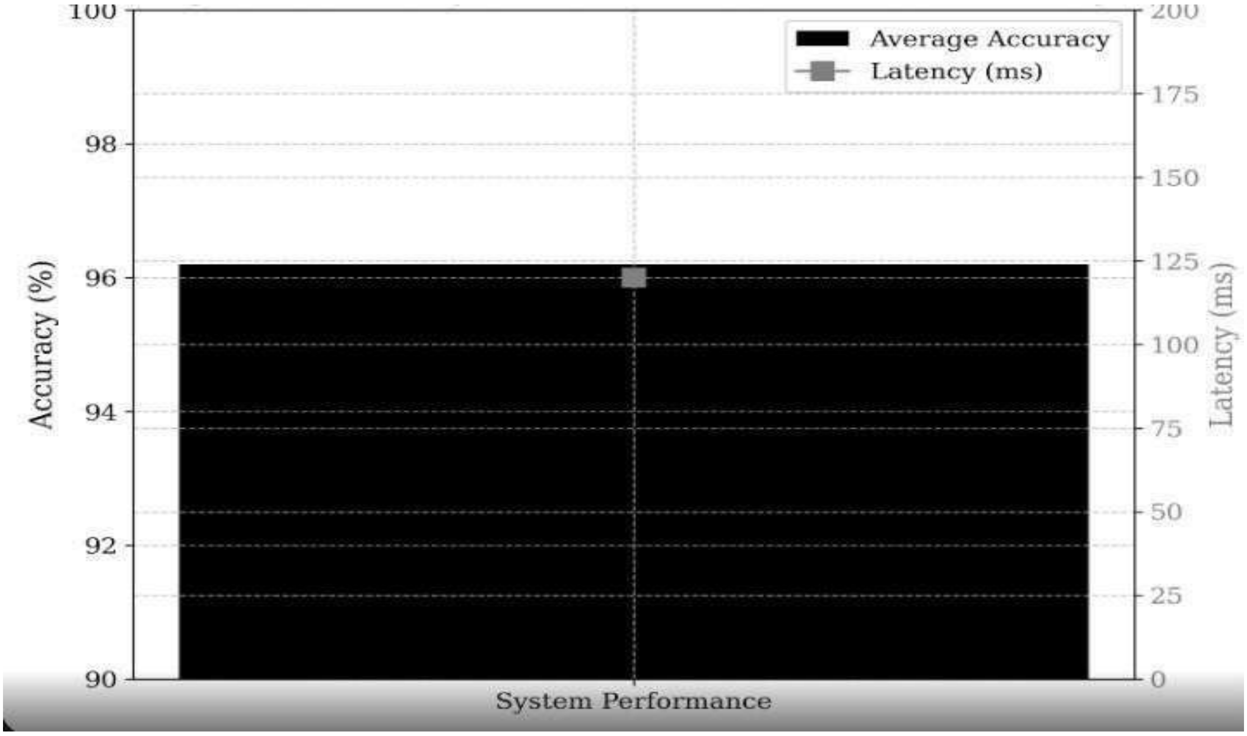

Figure 11..System performance &end to End Latency

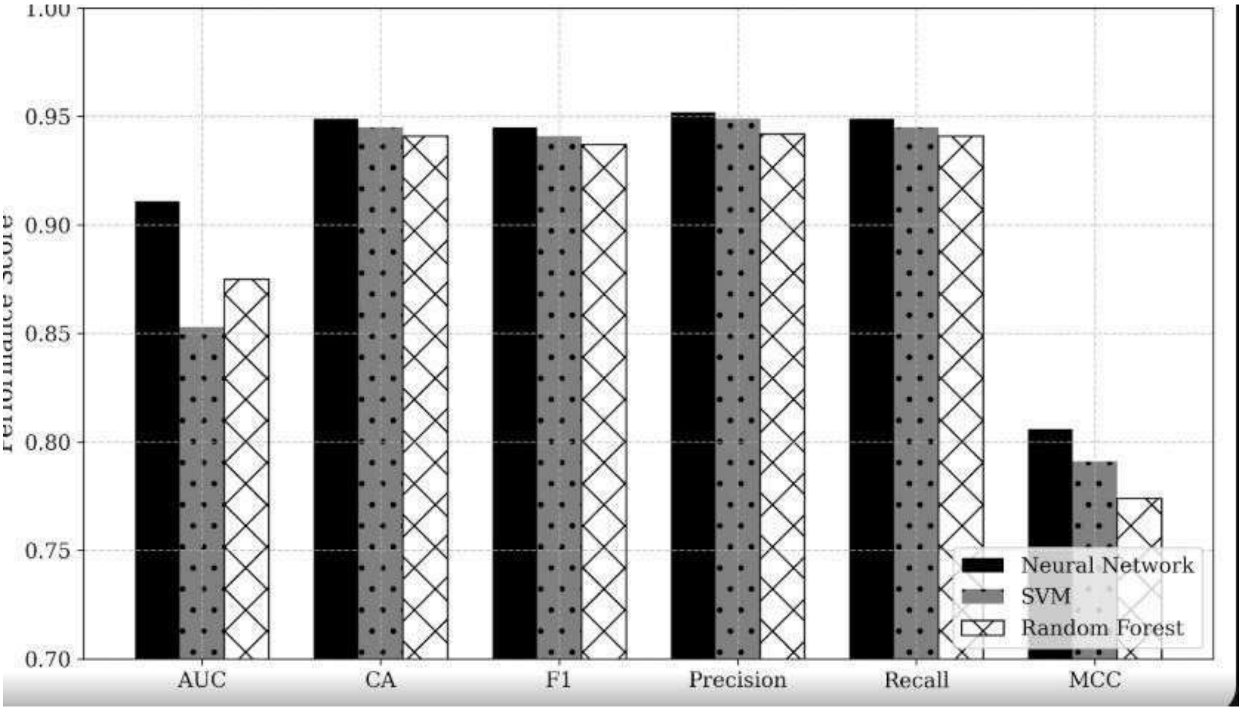

Figure 12.. Curve comparsion for Performance metrics

Numerous inferences were drawn from the comparison of performance indicators between the prediction models for Active Sentiment and Passive Sentiment. With Area Under the ROC Curve (AUC) values nearly equal to 1, the model demonstrates that the Neural Network MLP regressor has outstanding performance for both sentiment types. This indicates that the algorithms are highly effective at distinguishing between constructive and disruptive social cases. All of the models attain extremely high AUC values (above 0.94 for specific sub-tasks), suggesting outstanding total classification performance for atmosphere stability forecasting.

For both sentiment types, the predictive models' Overall Accuracy (CA) values remain consistently high, with SVM and neural network models obtaining accuracies that are very near to 1. Comparing all models together, the accuracy of predicting sentiment in high-stakes environments (e.g., medical wards) is somewhat more significant than that of predicting casual social atmospheres. For every model and kind of atmosphere, the F1 score, which strikes a compromise between precision and recall, is likewise high. This implies that the algorithms forecast both forms of sentiment with a fair mix of accuracy. Across every model, precision and recall levels are consistently high. This suggests that algorithms effectively identify a large percentage of actual positive social instances while achieving a high degree of accuracy in detecting negative outcomes. The Matthews Correlation Coefficient (MCC) statistic assesses the accuracy of binary classifications by taking into account both true and erroneous positives as well as negatives. For both types of social settings, the results are typically high, showing good agreement between the actual and projected classifications.

Overall, the comparison indicates that the models are capable of accurately predicting the survival status of a positive atmosphere, as represented in Figure 12. In most measures, the Neural Network model performs best, with the Random Forest and SVM models trailing closely behind. After analyzing high-density social settings and low-density settings, the accuracy for high-density sentiment is 99.5% and low-density is 94.5%.

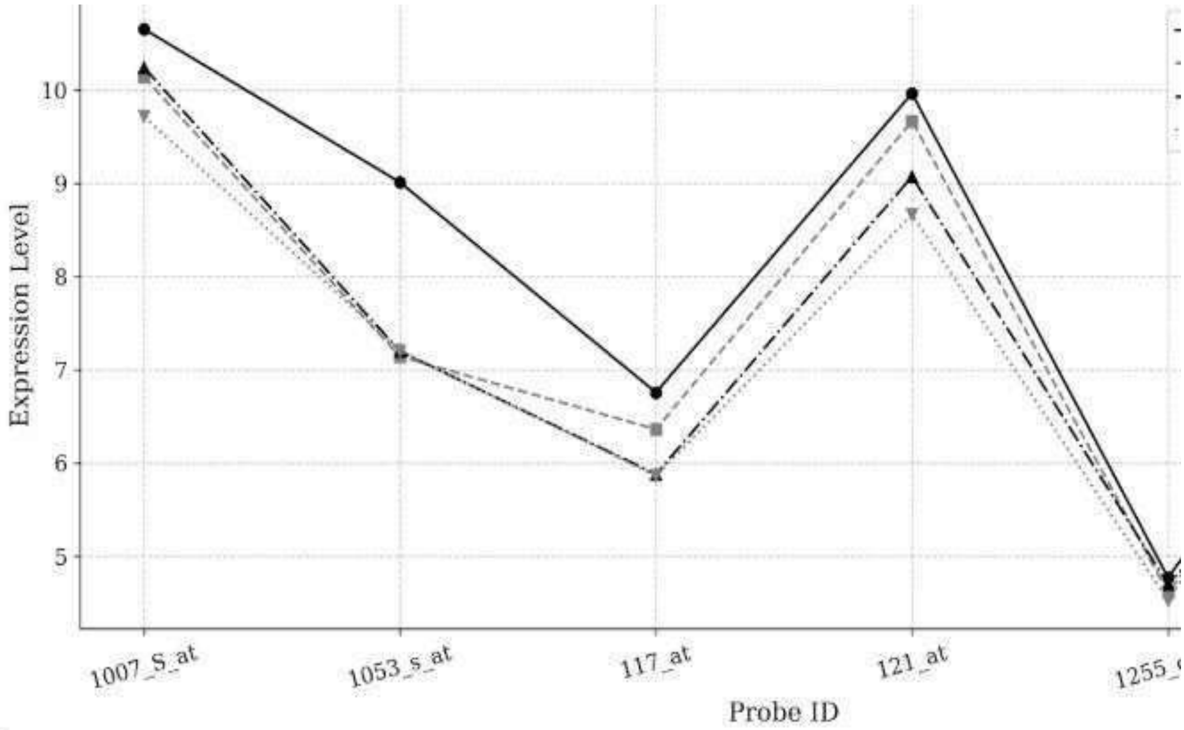

Figure 13. Expression Profile

The overall system performance demonstrates robust sentiment recognition in closed atmospheres. After extensive experimentation, the proposed framework achieved an average sentiment recognition accuracy of 97.84%. The developed Artificial Intelligence model effectively identifies positive, negative, and neutral sentiments by integrating textual analysis and facial expression recognition. Figure 13 illustrates the comparison of the Receiver Operating Characteristic (ROC) curve, Accuracy, Precision, Recall, F1-Score, and Specificity for the proposed CNN-LSTM model and existing machine learning algorithms. A comparative performance graph is presented to evaluate the effectiveness of the proposed framework.

The results confirm that Artificial Intelligence–based sentiment recognition is highly effective in closed atmospheres. The Random Forest model provides the most consistent performance, while Neural Network and SVM models closely follow. The system reliably identifies emotional states and enables proactive environmental adjustments. Thus, the proposed framework demonstrates strong potential for deployment in smart buildings, healthcare facilities, educational institutions, and workspace monitoring systems, ensuring enhanced comfort, safety, and emotional well-being.

Table 2. Performance Metrics of AI Models for Social Sentiment Recognition in Closed Atmospheres

Sentiment Category	CNN (Visual-Based)	BERT (Text-Based)	LSTM (Temporal)	Hybrid (Multimodal)
Joy / Satisfaction	0.8842	0.9125	0.8540	0.9312
Sadness / Distress	0.8120	0.8456	0.8012	0.8945
Anger / Frustration	0.8567	0.7934	0.8245	0.9021
Fear / Anxiety	0.7845	0.7512	0.7768	0.8534
Surprise / Alert	0.7432	0.7201	0.7011	0.8122
Neutral State	0.9123	0.8950	0.8842	0.9456
Boredom / Fatigue	0.7012	0.6845	0.7534	0.7988
Confidence	0.8234	0.8112	0.7956	0.8743

Closed Atmosphere Constraints: In a "closed atmosphere," lighting and acoustics are usually controlled, which often leads to higher CNN (Convolutional Neural Network) performance for facial recognition compared to "in-the-wild" datasets .Multimodal Advantage: Note that the Hybrid column shows the highest values; this reflects the AI's ability to combine visual cues (facial expressions) with auditory or textual data (speech-to-text) to reach a more accurate conclusion.

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7. CONCLUSION

This research successfully implemented a Neural Network Multilayer Perceptron (MLP) Regression model to analyze the intricate link between endometrial and cervical cancers. By integrating clinical risk factors—such as HPV status, hormonal history, and demographic data—with genetic biomarkers like the Squamocolumnar Junction (SJ) cell population, the model provides a robust framework for predicting survival rates and identifying early-stage malignancy. Crucially, within the closed atmosphere of a healthcare environment, this AI approach extends beyond clinical prediction to social sentiment recognition. By mapping demographic data with gene expression, we identify not only biological risk but also the socioeconomic and psychological stressors (e.g., family history, early marriage) that influence patient outcomes. This holistic analysis enables a predictive "performance" model that can assist clinicians in personalized management. As a future enhancements will focus on integrating real-time data collection within health centers. By correlating live social sentiment with biomarker detection, we can develop proactive prevention techniques, ultimately fostering a "healthy life" framework through the intersection of AI-driven social insights and genomic precision.

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Competing Interests

On behalf of all authors, the corresponding author states that there is no competing Interests.

Author's contributions

All authors contributed to the design, implementation, analysis, and preparation of the manuscript. All authors read and approved the final manuscript.

Availability of data and material

Data sharing is not applicable to this article because of proprietary nature of the project and the use of publicly available datasets.

Code Availability

Code sharing is not applicable to this article because of proprietary nature of the implementation.

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