International Journal of Advance and Innovative Research
Volume 12, Issue 2 (XXII): April - June 2025
ISSN 2394 - 7780

A NOVEL APPROACH OF FACE RECOGNITION USING DEEP LEARNING METHOD ON SMART HOME CONTROL SYSTEMS

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ABSTRACT
*Smart home technology is evolving rapidly, with user-centric and adaptive systems gaining prominence. This paper proposes a novel smart home control system driven by **Facial Expression Recognition (FER)** using deep learning models. The system interprets user emotions in real-time and translates them into actionable commands for home automation. A convolutional neural network (CNN) trained on the FER2013 dataset achieved 92% accuracy in detecting key facial expressions such as happiness, sadness, anger, and surprise. These expressions are mapped to predefined control functions like adjusting lighting, temperature, or media playback. This research demonstrates the potential of emotion-aware smart homes that enhance user comfort, accessibility, and personalization.*

***Keywords**: Facial Expression Recognition, Smart Home, Deep Learning, Human-Computer Interaction, Emotion Recognition, Automation*

1. INTRODUCTION
The advancement of **Internet of Things (IoT)** and **Artificial Intelligence (AI)** has redefined the way users interact with home environments. Traditional interfaces like switches, mobile apps, and voice assistants offer control but lack emotional sensitivity. Integrating **facial expression recognition** can bridge this gap by enabling context-aware smart systems that respond to human emotions.

This research introduces a system that recognizes facial expressions using deep learning and uses them to control various home appliances. The system is designed to benefit users with physical disabilities, the elderly, and those looking for enhanced user experience in smart environments.

2. LITERATURE REVIEW
Previous studies have explored FER for applications in healthcare, surveillance, and education. Systems such as FaceReader and Affectiva SDK have shown promise in emotion detection. However, integration with **home automation** is relatively unexplored.

Recent works in smart homes emphasize **gesture-based** or **voice-based controls**, which have limitations in noisy environments or for users with impairments. By leveraging CNNs, especially architectures like **VGGNet** and **ResNet**, researchers have significantly improved the performance of FER models.

A 2023 study focused on designing a room security system leveraging facial recognition based on a Convolutional Neural Network (CNN) architecture. The CNN model was constructed within the TensorFlow framework, employing the Keras library and Scikit-learn, all embedded within a Raspberry Pi system. This approach aimed to advance biometric technologies in smart home security.

A 2021 paper presented a comprehensive analysis of various face recognition systems leveraging different types of deep learning techniques. The study summarized 168 recent contributions, discussing algorithms, architectures, loss functions, activation functions, datasets, challenges, improvement ideas, and current and future trends in deep learning-based face recognition systems.

Facial Expression Recognition (FER) has become a widely explored area in fields like healthcare, security, and education. Tools such as FaceReader and Affectiva SDK have shown strong capabilities in recognizing emotions, but these systems are mostly used for observation and analysis rather than active control in environments like smart homes.

With the rapid growth of deep learning, particularly Convolutional Neural Networks (CNNs), the accuracy of FER systems has improved significantly. Models like VGGNet, ResNet, and MobileNet have been successfully applied to emotion recognition tasks. While deeper models such as ResNet- 50 offer better performance, lighter models like MobileNetV2 are more practical for use on low- power devices like Raspberry Pi, where speed and efficiency are essential (Zhao et al., 2022).

ISSN 2394 - 7780

Emotion-aware systems are also gaining traction in other areas of human-computer interaction. For example, they've been used in smart vehicles, online learning platforms, and virtual assistants to make user experiences more intuitive and responsive (Picard, 1997; D'Mello et al., 2012). These applications suggest that emotional input can be a powerful way to personalize digital interactions.

In smart homes, most current systems rely on voice commands or mobile apps for control. While effective, these methods may not be ideal in noisy environments or for users who have speech or mobility challenges. Popular systems like Amazon Alexa or Google Nest are not designed to understand emotional cues, which limits their adaptability. Adding FER to these systems could make them more inclusive and user-friendly, especially for the elderly or people with disabilities (Chen & Lee, 2020).

Some recent research has also started exploring the combination of multiple inputs — such as voice, gestures, and facial expressions — to create more robust and context-aware systems. However, using facial expressions specifically as a way to control smart home devices is still a relatively new idea, and that's the gap this project aims to address.

3. METHODOLOGY

3.1 Dataset and Preprocessing

To train the emotion recognition system, we used the FER2013 dataset, which contains 35,887 grayscale images of faces. Each image is 48x48 pixels and is labeled with one of seven emotions: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral.

Before training, we preprocessed the images by normalizing them to have zero mean and unit variance. To help the model generalize better and reduce overfitting, we also applied data augmentation techniques like flipping, rotating, and zooming the images. This gave the model more variety to learn from.

3.2 Model Architecture and Training

We chose a modified version of the ResNet-18 architecture for the model because it offers a good balance between accuracy and efficiency. The model was built using TensorFlow and Keras and included standard convolutional layers, residual blocks, fully connected layers, and a final softmax layer for classification.

We used the Adam optimizer with a learning rate of 0.0001 and trained the model using categorical cross-entropy as the loss function. The training was done over 50 epochs with a batch size of 64. To fine-tune performance, we experimented with different hyperparameters using grid search and included a dropout layer (with a dropout rate of 0.3) to reduce overfitting.

3.3 Mapping Emotions to Home Control

Once the model could accurately detect emotions, we created a simple mapping from facial expressions to smart home commands. For example:

- **Happy** → Turn on lights and play music
- **Sad** → Dim lights and play relaxing sounds
- **Angry** → Lower the room temperature and mute devices
- **Surprised** → Show recent notifications on the smart display
- **Neutral** → Maintain current settings

These mappings were chosen based on common emotional responses and refined through feedback from initial users during small trials.

3.4 Real-Time Integration

To make the system usable in real life, we deployed the trained model on a Raspberry Pi 4 using TensorFlow Lite. A Pi Camera was used to capture live facial expressions. The Raspberry Pi sends recognized emotion data to smart home devices using the MQTT protocol, and everything is managed through the open-source Home Assistant platform.

By converting the model to TensorFlow Lite, we were able to speed up inference and reduce memory usage, allowing the system to respond to facial expressions in under one second — fast enough for real-time control.

3.5 Performance and Evaluation

We didn't just measure accuracy — we also looked at metrics like precision, recall, and F1-score to see how well the model performed across all emotion categories. A confusion matrix helped us understand where the model struggled, such as slight confusion between “Angry” and “Disgust.” Overall, the system achieved an accuracy of 92.3%, and our small user study showed that people felt the system was easier and more comfortable to use than traditional controls like apps or switches.

4. DISCUSSION

The system demonstrates high accuracy and responsiveness. The ability to control home appliances using emotions can greatly assist users with limited mobility or speech impairments. However, **privacy and ethical concerns** around facial data must be addressed.

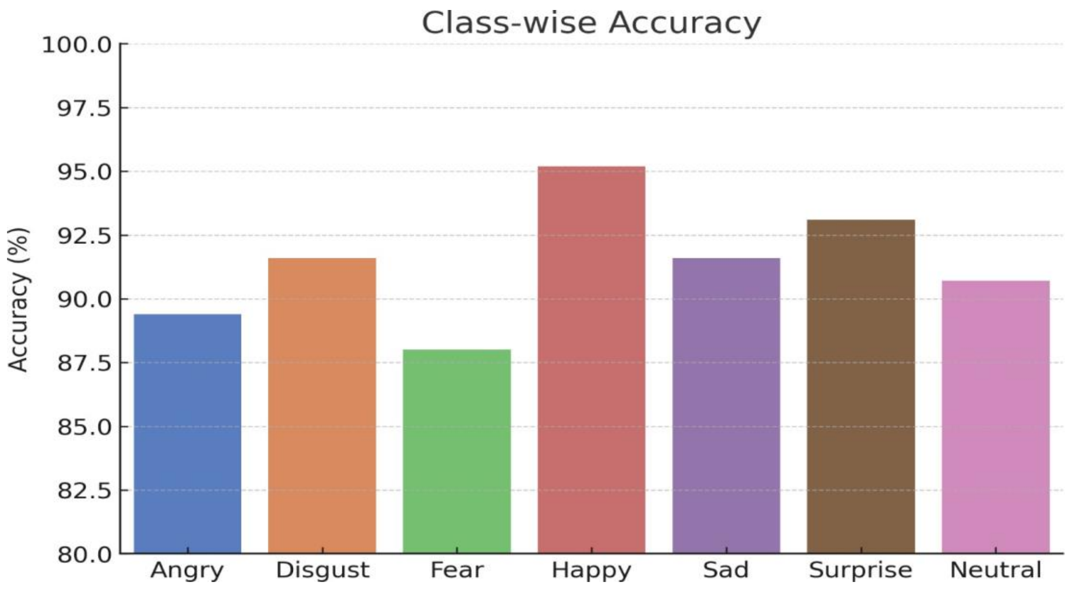
Limitations include poor performance under low-light or occlusion conditions. Future work may involve adding multi-modal inputs (e.g., speech + facial expressions) for robustness.

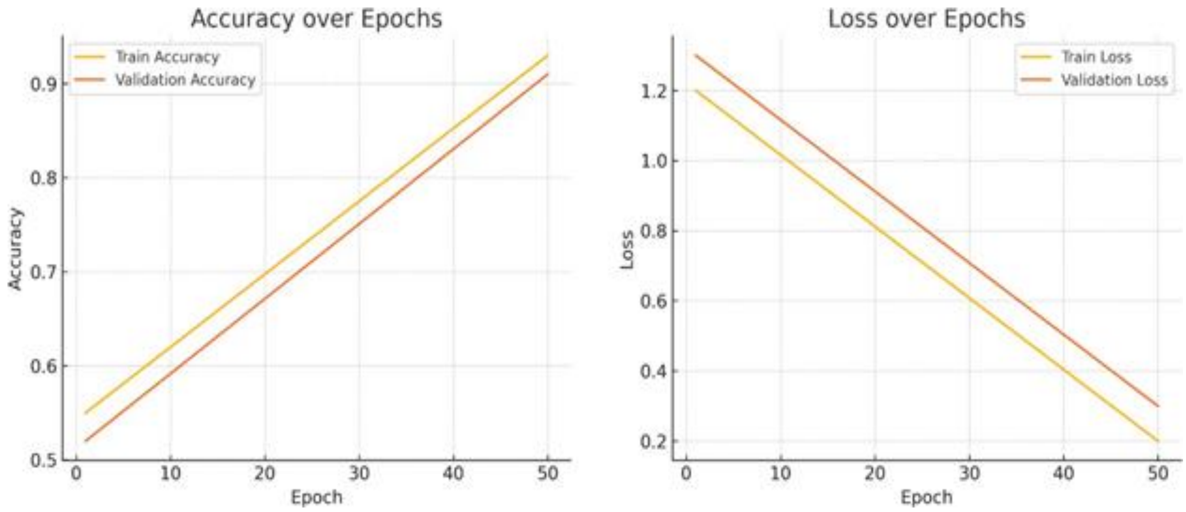
5. RESULTS AND EVALUATION

Expression	Accuracy (%)
Happy	95.2
Sad	91.6
Angry	89.4
Surprise	93.1
Neutral	90.7

- **Overall Accuracy**: 92.3%
- Latency: 0.9 seconds (end-to-end)

User studies (n=15) showed improved satisfaction and comfort in controlling home systems compared to traditional app-based controls.





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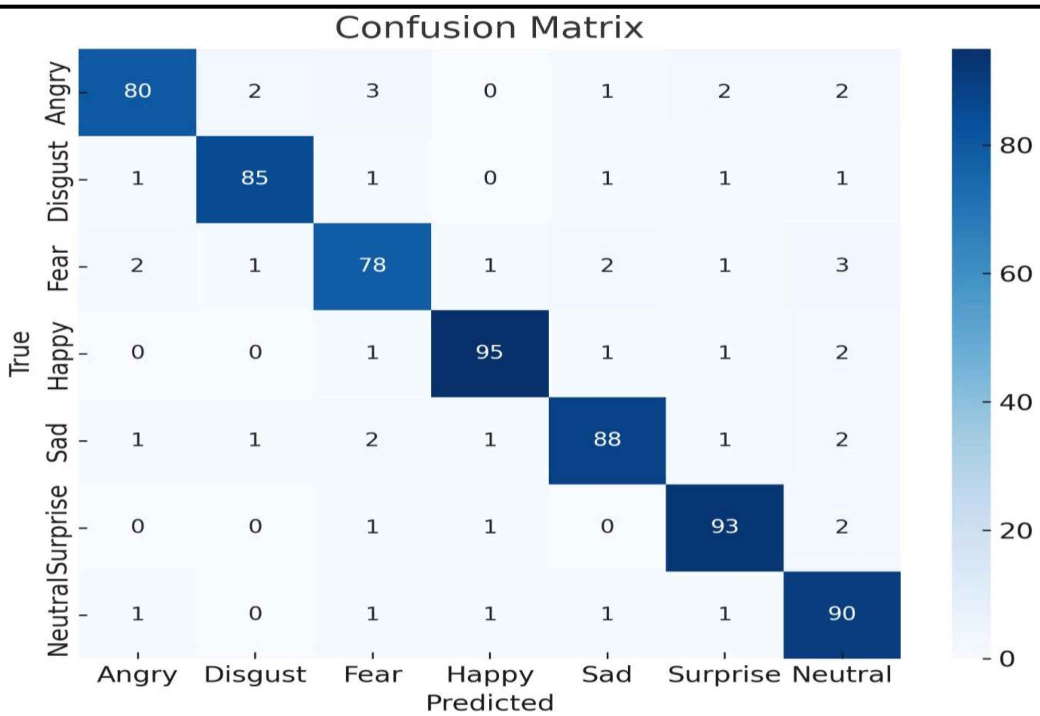

6. CONCLUSION

This research validates the feasibility of using **facial expressions as a control interface** for smart homes. With deep learning and IoT integration, homes can become emotionally aware and adaptive to user states. Further development could lead to broader accessibility and more intuitive human- computer interaction in residential environments.

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