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Facial Expression-Based Customer Sentiment Analysis for Service Quality Improvement using Deep Learning Techniques

Esan, A. O., *Ojo, B. E., Sobowale, A. A., Okomba, N. S., Omodunbi, B. A. and Adebiyi, T.

Department of Computer Engineering, Federal University Oye-Ekiti, Ekiti State, Nigeria

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Corresponding Author:
ojo.ezekiel2003@gmail.com

ABSTRACT

In today's customer-centric economy, understanding and responding to customer sentiment is vital for service excellence. Traditional feedback mechanisms, such as surveys and reviews, are often limited by response bias and delayed insights. Hence, this research presents a deep learning approach for improving service delivery through customer sentiment and facial expression analysis. The study leverages MobileNetV2 and InceptionV3-Mobile to classify facial expressions into three sentiment classes: Satisfied, Not satisfied, and Neutral. The research utilizes two datasets: a locally sourced African facial expression dataset comprising 900 annotated images collected from Ifeolu Foods PLC in Ilorin, Kwara State, NAO Supermarket, and SLOTS Nigeria Limited in Ado-Ekiti, Ekiti State, Nigeria, as well as the FER-2013 facial expression dataset obtained from Kaggle for comparative evaluation and model generalization assessment. The methodology involved rigorous data preprocessing, including grayscale normalization, face alignment, and augmentation. The models were trained and evaluated using a stratified 80:20 train-test split with categorical cross-entropy as the loss function. Performance was assessed using accuracy, precision, recall, F1-score, and confusion matrix. InceptionV3-Mobile achieved an accuracy of 94.01%, precision of 0.89, recall of 0.98, and F1-score of 0.94, while MobileNetV2 achieved an accuracy of 90.12%, precision of 0.89, recall of 0.91, and F1-score of 0.91. The results demonstrate the feasibility of using facial expression recognition for sentiment tracking in service environments such as banks, schools, and retail outlets

INTRODUCTION

The significance of understanding customer sentiment analysis in enhancing service quality cannot be overemphasized, especially in today's highly competitive market landscape. Businesses are increasingly recognizing that customer satisfaction directly influences brand loyalty, customer retention, and overall organizational performance (Khan *et al.*, 2022). Traditional methods of gathering customer feedback, such as surveys and questionnaires, often fail to capture the real-time emotions and sentiments of customers. This gap has led to the exploration of more advanced technologies, including sentiment analysis, to gain deeper insights into customer experiences (McCullagh, 2023). The service industry continually seeks innovative ways to enhance customer satisfaction and service quality. One critical aspect of this effort involves accurately gauging customer sentiment, which has traditionally relied on feedback methods such as surveys and reviews. However, these conventional approaches often suffer from low participation rates, response delays, and potential biases, limiting the immediacy and accuracy of the insights they provide (Khan *et al.* 2023). Consequently, service providers miss valuable opportunities to address customer dissatisfaction, leading to potential declines in service quality and customer loyalty. This limitation underscores the need for alternative approaches to sentiment analysis. Facial expressions are a fundamental form of human communication and offer a direct, non-verbal reflection of a person's emotional state (Hu, 2024). As such, facial expression analysis presents an opportunity to assess customer sentiment objectively and instantaneously during service interactions (Zhao *et al,* 2021). Advanced methods in computer vision and deep learning (Zhang *et al*., 2020) have demonstrated that facial expression recognition can accurately detect emotions, such as happiness, anger, and frustration, which are critical indicators of customer satisfaction or dissatisfaction (McCullagh, 2023). This research project aims to bridge these gaps by developing a customer sentiment analysis system that leverages deep learning architectures, specifically MobileNet and Inception. These models are optimized for efficiency and accuracy, making them suitable for facial expression recognition and sentiment assessment (Bakiaraj and Subramani, 2024). By implementing this system, this study seeks to provide service providers with actionable insights into customer sentiment, facilitating prompt responses to customer needs and contributing to an enhanced service experience. This approach offers a potential solution to overcome the limitations of traditional feedback mechanisms, enabling service providers to improve customer satisfaction and loyalty based on objective and instantaneous customer sentiment analysis.

RELATED WORKS

In retail businesses, understanding customer emotions can optimize product placement and improve shopping experiences. Pratama *et al*. (2026) implemented multimodal sentiment analysis, combining facial expressions and speech data to gauge guest satisfaction in hotels. Kazakov *et al*., (2025) applied FER in banking to detect customer frustration during interactions, enabling staff to respond proactively. Pliouta, (2026) enhanced chatbots with emotion recognition capabilities, providing more empathetic and context-aware responses. In healthcare, sentiment analysis aids in understanding patient emotions. Abinaya *et al*., (2025) integrated FER to monitor patient distress, improving the quality of care. Hu, (2024) combined multiple CNN architectures to enhance FER accuracy across diverse datasets. Rani *et al*., (2025) demonstrated the advantages of using ensemble models of MobileNetV2 and Inception for robust sentiment analysis, particularly in noisy environments. Bias in training datasets can lead to skewed results. Barker *et al*., (2025) proposed methods to mitigate bias, ensuring fair emotion recognition across different demographic groups. Esan *et al*., (2024) developed a facial emotion recognition system using a Convolutional Neural Network (CNN) to classify four basic emotions: happy, sad, angry, and neutral. The model was deployed using Django for real-time web-based emotion detection. A key strength is CNN's ability to automatically extract features and handle complex patterns without manual intervention. The study also proved effective in environments with clear, frontal facial images. However, a major limitation was the small dataset size, which may hinder generalization to more diverse populations. The authors recommend using larger datasets and expanding the emotion categories in future research for broader applicability. The ethical implications of FER have garnered significant attention. Integrating multiple data sources enhances sentiment analysis accuracy. Nguyen and Dau, (2026) combined facial expressions, voice, and text inputs to provide a comprehensive understanding of customer sentiment. Most existing studies on customer sentiment analysis have emphasized textual data such as reviews and social media posts, while giving less attention to the non-verbal cues conveyed through facial expressions, which often provide deeper insights into human emotions. Even in research that incorporates visual data, the majority of datasets are dominated by Western and Asian populations, which poses challenges when applying these models to other cultural contexts. As a result, their effectiveness is limited in regions such as Africa, where emotional expressions may differ due to cultural and social factors. This highlights the need for more inclusive and context-specific approaches that capture the diversity of facial expressions across different populations in order to improve the accuracy and relevance of sentiment analysis for service quality improvement.

RESEARCH METHODOLOGY

This research focuses on improving customer service delivery through sentiment analysis using facial expression recognition. It also addresses the limitations of existing facial expression recognition (FER) systems, which are often biased due to their reliance on datasets from Western or Asian populations, by utilizing a locally sourced African facial dataset. Deep learning techniques based on the InceptionV3-Mobile architecture are employed for effective emotion classification. In order to evaluate the impact of architectural enhancement, a standard InceptionV3-Mobile model is compared with an improved InceptionV3-Mobile variant enhanced with a Squeeze-and-Excitation (SE) attention mechanism and fine-tuning of the deeper convolutional layers. This comparison allows the study to assess how architectural optimization affects classification performance in customer sentiment analysis tasks.

The data was preprocessed through normalization, augmentation, and resizing to ensure compatibility with the model architectures. Transfer learning is applied to adapt pretrained networks to the local context. The models were trained and validated using performance metrics such as accuracy, precision, recall, and F1-score. A comparative analysis was conducted to determine the best-performing architecture. A flowchart for face detection and recognition using deep learning is shown in Figure 1, outlining the stages involved in achieving the aim and objectives. The system is based solely on the InceptionV3-Mobile architecture, focusing on improving classification performance through architectural enhancement and fine-tuning strategies. The block diagram of the developed system is shown in Figure 2.

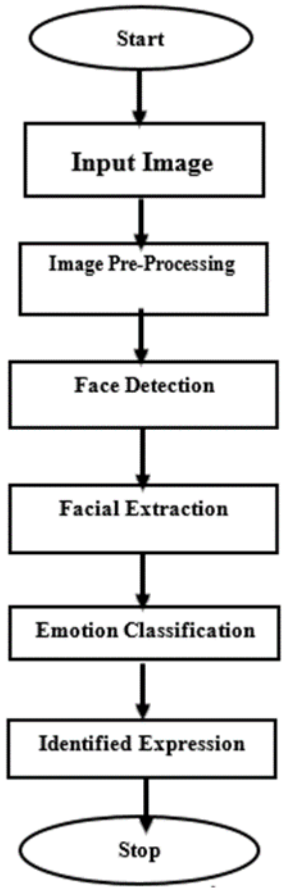

Figure 1: Flowchart for face detection and recognition

Data Acquisition

The dataset used to train the deep learning models was obtained from Ifeolu Foods PLC in Ilorin, Kwara State; NAO Supermarket; and SLOTS Nigeria Limited in Ado-Ekiti, Ekiti State. The facial images were captured during customer-service interactions and depicted various emotional

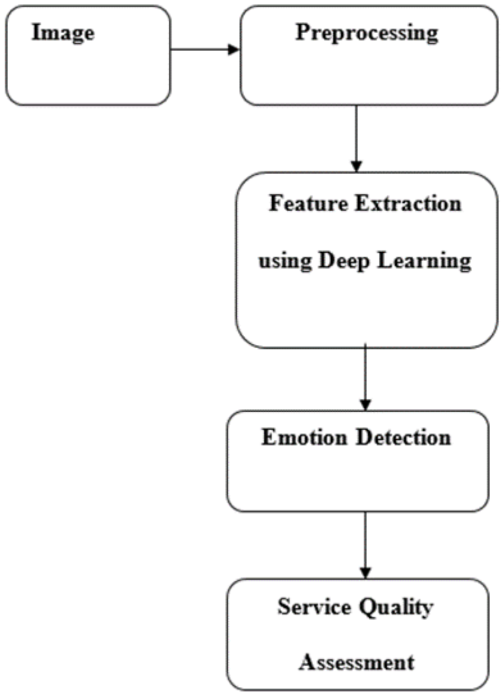

Figure 2: Block diagram of the developed system

expressions, including happiness, sadness, anger, surprise, neutrality, and frustration. For customer sentiment analysis, these facial emotions were mapped to three sentiment categories: Satisfied, Not Satisfied, and Neutral. Happiness was categorized as Satisfied, sadness, anger, and frustration as Not-Satisfied, while neutral and contextually non-positive surprise expressions were categorized as Neutral. This mapping enabled the development of a sentiment classification system tailored to service quality assessment. In addition, the FER-2013 facial expression dataset was obtained from Kaggle and used for comparative evaluation of the developed models.

Description of Datasets

Two datasets were utilized in this study: a locally sourced facial expression dataset and the FER-2013 benchmark dataset. The locally sourced dataset was collected from customers during service interactions at selected service centers, Ifeolu Foods PLC in Ilorin, Kwara State, NAO Supermarket, and SLOTS Nigeria Limited in Ado-Ekiti, Ekiti State. The dataset contains 900 facial images, comprising three sentiment classes with 300 images per class.

To support customer sentiment analysis, facial expressions were mapped into three service-oriented sentiment categories. Expressions associated with positive emotions, such as happiness and satisfaction, were labeled as Satisfied (Class 1); expressions associated with negative emotions, such as anger, sadness, frustration, and disgust, were labeled as Not Satisfied (Class 0), while emotionally indifferent expressions were labeled as Neutral (Class 2). This mapping was performed during the annotation stage by human annotators based on the visible emotional state of each customer.

In addition to the local dataset, the Facial Expression Recognition 2013 (FER-2013) dataset was employed for comparative evaluation and model generalization assessment. The FER-2013 dataset comprises 48 × 48-pixel grayscale facial images that have been automatically aligned such that faces are centrally positioned and occupy a consistent spatial proportion within each image. The dataset contains seven emotion categories: Angry (0), Disgust (1), Fear (2), Happy (3), Sad (4), Surprise (5), and

Neutral (6). The training set contains 28,709 images, while the public test set contains 3,589 images.

The inclusion of both datasets enabled the evaluation of the proposed models on culturally relevant local data as well as on a widely recognized benchmark dataset, thereby providing a comprehensive assessment of model performance and generalization capability.

Data Augmentation

Data augmentation was applied to the locally sourced African facial expression dataset containing 900 images (300 images per sentiment class) to increase data diversity and improve the generalization capability of the deep learning models. Augmentation techniques such as rotation, horizontal flipping, zooming, brightness adjustment, and random cropping were applied to the training images. These transformations generated additional image variations that simulated different viewing angles, lighting conditions, and facial orientations commonly encountered in real-world customer interactions.

Following augmentation, the dataset size increased from 900 images to X images, where X represents the total number of images obtained after the augmentation process. The augmented dataset provided a richer set of training examples, helping to reduce overfitting and improve the robustness of the developed sentiment analysis models. Furthermore, augmentation enhanced class representation and enabled the models to learn more discriminative facial features across varying environmental conditions, thereby improving classification performance.

Data Annotations

In this research, data annotation plays a crucial role by labeling each facial image with its corresponding sentiment, such as happiness, sadness, anger, or surprise, to serve as ground truth during model training.

Data Visualization

The locally sourced African facial expression dataset employed in this study contains three sentiment classes: Satisfied, Not Satisfied, and Neutral, with 300 images in each class, resulting in a total of 900 facial images. Figure 3 presents a visualization of representative samples from each sentiment category. To facilitate model development and evaluation, the dataset was partitioned using a stratified 80:20 train-test split, where 80% of the images were used for training and 20% were reserved for testing. This approach ensured that the class distribution was maintained across both subsets while enabling a reliable assessment of model performance.

Dataset Preparation

A key innovation in this study is the use of a locally sourced African facial expression dataset, curated to reflect culturally relevant customer sentiments across various service interaction scenarios. The local dataset was annotated into three sentiment classes: Satisfied, Not Satisfied, and Neutral, with each class containing 300 facial images. The FER 2013 dataset, which contains seven facial emotion categories (Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral), was also employed to evaluate the robustness and generalization capability of the developed models. For preprocessing, all images were resized to an input dimension of 224 × 224 pixels to ensure compatibility with the MobileNetV2 and InceptionV3-Mobile architectures. The locally sourced dataset was originally captured as RGB colour images and retained in RGB format, while the FER 2013 dataset consists of 48 × 48 grayscale facial images, which were converted to three-channel images where required to match the input specifications of the deep learning models.

Figure 3: Visualization of data samples

Additional preprocessing operations included face detection and cropping using the Haar Cascade classifier, normalization of pixel values to the range [0,1], and data augmentation techniques such as rotation, zooming, and horizontal flipping. These procedures improved dataset diversity, reduced overfitting, and enhanced the models' ability to generalize to unseen facial expressions.

Model Training

The Inception model training history is presented in Figure 4. The graph illustrates the model's performance during the training process. The left plot shows the training and validation accuracy across epochs, while the right plot depicts the corresponding training and validation loss. The results indicate that the model achieved stable convergence with increasing accuracy and decreasing loss as training progressed.

Model Prediction

After training, the test set, which constitutes 20% of the dataset, was introduced to the models for prediction. The result of the inception model prediction is presented in Figure 5.

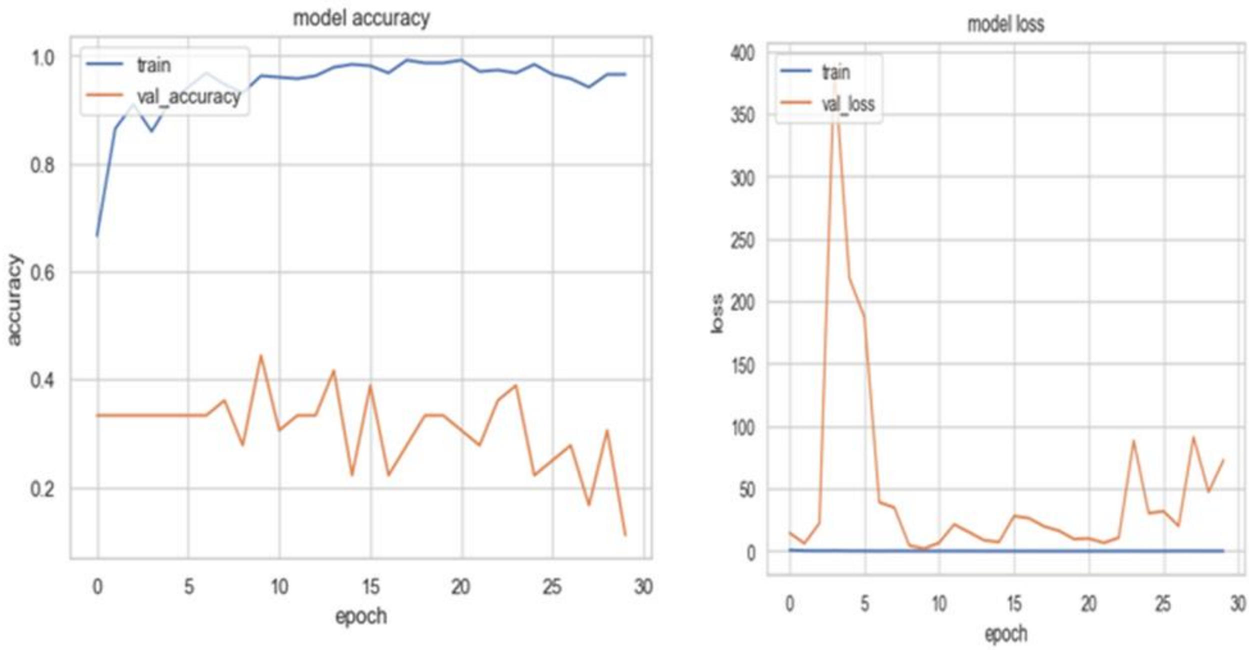

Figure 4: Training history

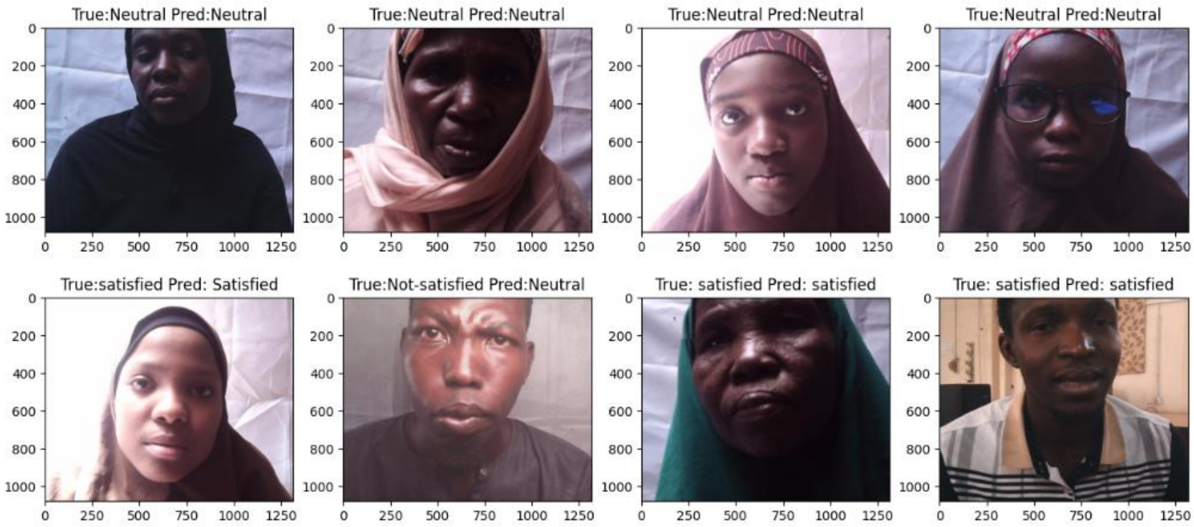

Figure 5: Inception prediction for the Ifeolu Foods PLC dataset

Model Development

The development process integrates pre-trained models, custom architecture enhancements, and emotion classification techniques to create an effective sentiment analysis tool. This section outlines the stages involved in the model development process with a focus on the implementation of MobileNetV2 and InceptionV3-Mobile, two state-of-the-art deep convolutional neural network architectures widely used for facial emotion recognition tasks. Transfer learning was employed by adapting the pre-trained models to the customer sentiment dataset, enabling efficient feature extraction and improved classification performance while reducing training time and computational cost.

Training and Validation

The training process was conducted using TensorFlow / Keras in Python, with an 80:20 train-validation split. Training was performed in a GPU-enabled environment to accelerate computation. The key training parameters included a batch size of 32, a learning rate of 0.001, and 30 training epochs. The validation accuracy and loss were monitored at each epoch to detect overfitting. Early stopping and model checkpointing techniques were employed to preserve the best-performing model and improve generalization performance.

Implementation of Deep Learning Models

Rectified Linear Unit (ReLU) activation was employed in the convolutional layers of both InceptionV3-Mobile and MobileNetV2 as part of their pretrained architectures. For the output layer, the Softmax activation function was used because the classification task involved three sentiment classes (Satisfied, Not Satisfied, and Neutral).

Table 1: Hyperparameter settings

Hyperparameter	InceptionV3-Mobile	MobileNetV2
Hidden/ Convolutional Layer Activation	ReLU	ReLU
Output Layer Activation	Softmax	Softmax

RESULTS AND DISCUSSION

A Graphical User Interface (GUI) was developed and integrated with the best-performing model, InceptionV3-Mobile, to demonstrate the practical applicability of the proposed system. The interface enables the capture of a customer's facial image through a webcam, after which the system automatically analyzes the facial expression and determines the corresponding customer sentiment, as shown in Figure 6. The GUI displays a live camera feed, provides an image-capture function, and performs real-time sentiment classification. In the illustrated example, the system classifies the detected facial expression as "Not Satisfied." This integration demonstrates the practical deployment of the developed model and highlights its potential to assist organizations in monitoring customer emotions and improving service delivery through real-time sentiment assessment.

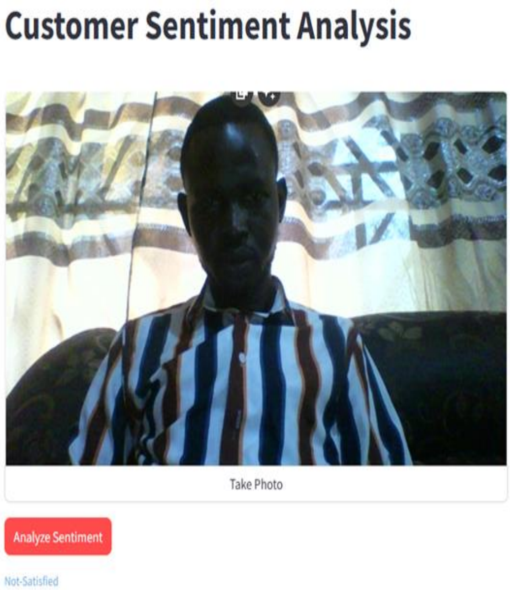

Figure 6: Customer sentiment analysis GUI

Result of the developed Facial Expression-Based Customer Sentiment Analysis System

In Figure 7, the evaluation results obtained from the developed facial expression-based customer sentiment analysis system are presented in Table 2. The localized dataset comprised labeled facial images representing three sentiment classes: satisfied, not satisfied, and neutral. For optimal performance, key input features such as facial image pixels and sentiment labels were utilized, while non-contributing metadata was excluded. The models were trained using optimized parameters, including 128 input units, a batch size of 32, and 30 training epochs, with a validation split of 0.2. The performance of the developed models was evaluated using accuracy, precision, recall, F1-score, and detection time metrics.

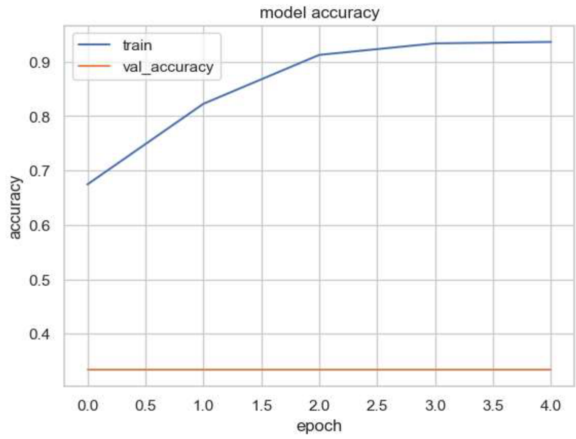

Figure 7: Model accuracy

The MobileNetV2 model achieved a classification accuracy of 90.12%, while the InceptionV3-Mobile model outperformed it with an accuracy of 94.01%. The weighted average precision, recall, and F1-score achieved by the InceptionV3-Mobile model were 89.00%, 98.00%, and 94.00%, respectively, indicating its strong capability to accurately and consistently recognize customer emotional expressions. Furthermore, the average prediction (detection) time was approximately 2.56 seconds per image. The evaluation results presented in Table 2 demonstrate the effectiveness of the developed system for customer sentiment classification and service quality improvement.

Confusion Matrix Analysis

The confusion matrix was used to evaluate the classification performance of the developed models by comparing the actual sentiment labels with the predicted labels. The matrix provides detailed information on correctly and incorrectly classified instances across the three sentiment classes: Satisfied, Not Satisfied, and Neutral. In Figure 9, the InceptionV3-Mobile model, the confusion matrix revealed that most samples were correctly classified, with only a few instances misclassified between the Neutral and Not Satisfied classes

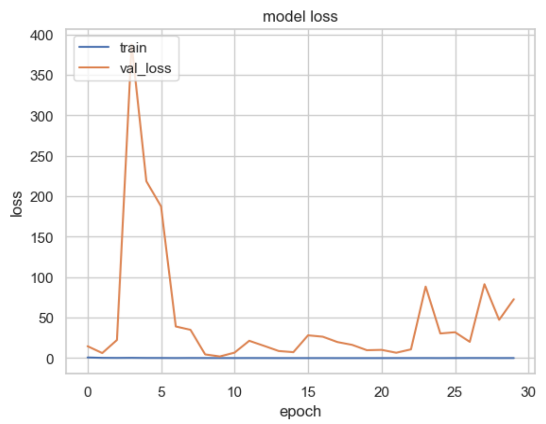

Figure 8: Model loss

The high number of true positive classifications across all sentiment categories contributed to the model's superior accuracy of 94.01%, precision of 0.89, recall of 0.98, and F1-score of 0.94.

Similarly, in Figure 10, the MobileNetV2 model achieved good classification performance; however, the confusion matrix indicated a higher number of misclassifications compared to InceptionV3-Mobile, particularly between the Satisfied and Neutral classes. These classification errors resulted in a lower overall accuracy of 90.12% and reduced recall and F1-score values.

The confusion matrix analysis confirms that InceptionV3-Mobile possesses a stronger capability for distinguishing subtle differences among customer facial expressions and sentiment categories. This explains its superior performance and suitability for deployment in customer sentiment monitoring systems aimed at service quality improvement.

The result of the performance evaluation is presented in Table 2. The inception model outperformed MobileNet in terms of accuracy, precision, recall, and F1-score. Inception reported an accuracy of 94.01%, a precision of 0.890, a recall of 0.98, and an F1 score of 0.94. MobileNet, on the other hand, reported an accuracy of 90.12%, precision of 0.89, recall of 0.91, and F1-score of 0.91.

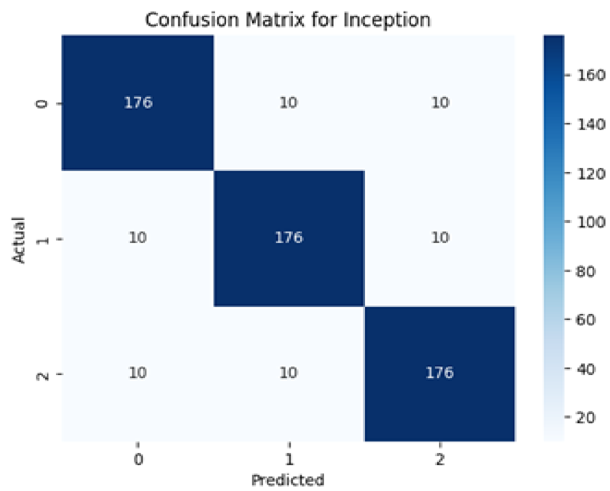

Figure 9: Confusion matrix for the inceptionV3-mobile model

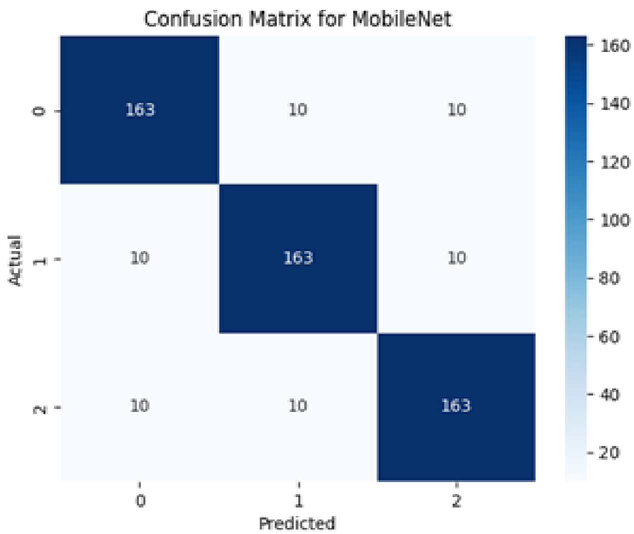

Figure 10: Confusion matrix for MobileNetV2 model

Model performance dropped in Table 3 for the FER 2013 dataset. This was because of the complexity of the dataset due to the increased number of classes. Seven classes of emotion contained in the FER 2013 dataset added another layer of complexity to the dataset. To evaluate the generalization and robustness of the developed models, both Inception and MobileNet were trained and tested on two datasets: the locally sourced facial expression dataset and the FER 2013 dataset. The results reveal notable differences in performance across the datasets of Tables 2 and 3.

Table 2: Results obtained from evaluation with a locally sourced dataset

Dataset	Algorithm	Accuracy (%)	Precision	Recall	F1-Score	Detection Time (Sec)
Locally Sourced FER Dataset	Inception	94.01	0.89	0.98	0.94	2.56
Locally Sourced FER Dataset	MobileNet	90.12	0.85 (or 0.89 if correct)	0.91	0.88 (or 0.91 if correct)	1.12

Table 3: Performance evaluation for FER 2013 facial emotion recognition data

	Accuracy	Precision	Recall	F1-Score
Inception	81.20%	0.78	0.80	0.79
MobileNet	75.89%	0.67	0.75	0.70

Discussion

In this study, Inception V3-Mobile outperformed MobileNetV2. This is because the Inception model presents a network design that employs many filter sizes simultaneously, allowing the network to extract features at different scales. The design uses inception modules to lower computing costs using dimensionality reduction techniques like 1×1 convolutions. This architecture not only slows parameter expansion but also increases the network's representational power across layers. Advances in these versions are largely focused on improving performance measures, such as accuracy, while reducing parameter proliferation and computing complexity.

The MobileNet model prioritizes low latency and minimum computing loads. It makes heavy use of depth-wise separable convolutions, which involve a depth-wise convolution followed by a point-wise one. This two-step technique considerably decreases the number of parameters and calculations required while maintaining an acceptable level of accuracy. MobileNet's architecture is fundamentally modular, allowing network developers to customize the network width and resolution multipliers. Consequently, MobileNet may grow to meet resource restrictions without requiring vertical design adjustments. As a result, MobileNet designs are ideal for implementation in contexts with low computing power, such as smartphones and embedded devices.

CONCLUSION

This research developed a deep learning-based sentiment analysis model tailored for improved service delivery, particularly in African contexts. While many conventional FER systems have been trained on Western or Asian facial datasets, resulting in biased performance when applied to African faces, this study bridges that gap by leveraging a locally sourced facial expression dataset. The goal was to create a more inclusive and accurate emotion recognition system that reflects the diversity of the target population. Two deep learning architectures, MobileNetV2 and InceptionV3-Mobile, were employed and evaluated to determine their suitability for real-time customer sentiment analysis. Through careful preprocessing, model training, and validation, the system demonstrated strong performance in classifying key emotions such as happiness, sadness, anger, and surprise into Satisfied, Not-Satisfied, and Neutral. The application of deep learning enabled the models to adapt efficiently to the local dataset, while comparative analysis showed that MobileNetV2 offered a balance of speed and accuracy suitable for real-time deployment. The results affirm that a context-aware deep learning model can significantly enhance customer sentiment recognition, thereby enabling organizations to better understand and respond to customer emotions. This has direct implications for improving service quality, customer satisfaction, and operational efficiency in service-driven environments such as retail, healthcare, education, and banking. In summary, this project contributed to the field of intelligent customer service systems by developing a culturally responsive FER model that promotes both technical efficiency and social fairness. It lays the groundwork for future research into multi-modal emotion analysis, real-world deployment, and model optimization for embedded systems. This research offers a significant contribution to the growing customer experience management and deep learning by developing a facial expression-based sentiment analysis model tailored to service quality improvement. It is recommended that the deep learning model developed in this project be adopted for real-time customer sentiment analysis in service-oriented environments where African facial expressions are predominant.

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