AI-Based Biscuit Defect Detection System for Enhancing Food Industry Quality Control

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ABSTRACT

The quality control of biscuits in large-scale food manufacturing is a critical factor in ensuring customer satisfaction and brand reputation. Traditional manual inspection methods are time-consuming, prone to human error, and lack consistency, particularly when detecting subtle defects. To address these limitations, this research proposes a AI-Based Biscuit Defect Detection System for Enhancing Food Industry Quality Control is designed to automatically identify and classify biscuit defects using machine learning and deep learning techniques. In traditional food manufacturing industries, biscuit quality inspection is typically performed manually, which can be time-consuming, inconsistent, and prone to human error. To address this challenge, the proposed system utilizes image processing and artificial intelligence to analyze biscuit images and detect defect categories such as Color Defect, No Defect, Object Defect, and Shape Defect. The dataset is first preprocessed through image resizing, normalization, and conversion into numerical arrays to prepare it for model training. Multiple classification models including Extra Trees Classifier (ETC), Linear Discriminant Analysis (LDA), and Light Gradient Boosting Machine classifier (LGBM) are implemented and compared with a proposed ResNet-based Convolutional Neural Network (CNN) model that automatically extracts complex visual features from biscuit images. The models are evaluated using performance metrics such as Accuracy, Precision, Recall, and F1-score, along with visualization techniques including confusion matrices and ROC-AUC curves to measure classification effectiveness. Experimental results demonstrate that the ResNet CNN model achieves superior performance with an accuracy of approximately 98.98%, significantly outperforming traditional machine learning models. The system is implemented with a user-friendly graphical interface that supports dataset management, model training, prediction, and result visualization, along with additional capabilities such as batch prediction and Telegram bot integration for remote biscuit quality analysis. The proposed system provides an efficient, automated, and reliable solution for biscuit defect detection, helping food industries improve product quality control, reduce manual inspection efforts, and ensure consistent manufacturing standards through intelligent image-based analysis.

Keywords: Biscuit Defect Detection, Quality Control in Food Industry, Deep Learning, Convolutional Neural Network (CNN), Automated Inspection System

1. INTRODUCTION

Quality control in the food industry is critical for ensuring product standardization and enhancing customer satisfaction. However, manual quality control processes are time-consuming, costly, and prone to human error, increasing the demand for automation systems. Advances in artificial intelligence and computer vision technologies offer a significant solution by enabling the automation of these processes. In traditional biscuit production lines, quality control is typically carried out through manual visual inspection or simple optical sensors. Manual inspection, although flexible, is labour-intensive, time-consuming, and highly dependent on the operator's concentration and experience, leading to inconsistencies and missed defects. Optical systems, on the other hand, often rely on predefined threshold values for color or shape and are unable to adapt to new or complex defect types without manual recalibration as shown in figure 1. Moreover, these systems struggle with overlapping or ambiguous defects, which further limits their effectiveness. According to observational data and case studies from the industry, defect rates in biscuit production can vary significantly depending on production conditions, process stability, and the level of automation. This highlights the need for more adaptive and accurate inspection solutions, especially those capable of generalizing across diverse defect scenarios with minimal human intervention.

Fig.1: Quality inspection of Biscuits.

Traditional quality control in the biscuit industry is primarily manual, involving human inspectors who visually check for surface defects, deformities, and other inconsistencies. However, human inspection is often limited by fatigue, inconsistency, and subjectivity. A study by the Journal of Food Engineering indicated that human-based inspection systems in manufacturing have an average error rate of 20% due to environmental, cognitive, and procedural variability. Such inconsistencies not only increase the chances of defective items reaching consumers but also add to operational costs through recalls and reputation damage. The integration of computer vision with advanced image processing and machine learning has enabled automated defect detection across industries. In food manufacturing, computer vision provides real-time, non-invasive, and high-speed inspection, making it a valuable alternative to traditional methods.

2. RELATED WORK

The evolution of food science and agricultural systems has been significantly influenced by advancements in food processing, nutrition analysis, and sustainable resource utilization. Early research primarily focused on the efficient utilization of agricultural by-products and improving food quality through innovative processing techniques. Castagna et al. [1] highlighted extraction, composite production, and bioconversion as key strategies for valorizing agricultural waste. Their study emphasized the role of digitalization in enhancing efficiency while also addressing the challenges associated with waste utilization.

2.1 Food Processing and Optimization Techniques

Optimization of food production processes has gained importance in improving quality and efficiency. Păcală et al. [2] applied fuzzy logic modeling to optimize lactic fermentation in buckwheat-based substrates under different processing conditions. Similarly, Purlis et al. [3] analyzed food breakdown during oral processing, emphasizing the role of water as a plasticizer affecting structural and mechanical properties. These studies underline the importance of modeling and optimization in food engineering systems.

2.2 Recommendation Systems and Consumer Preferences

Understanding consumer preferences has become a critical factor in food-related systems. Song et al. [4] discussed traditional recommendation systems that rely on popularity and user ratings, highlighting their limitations in addressing individual sentiment variations. Siddiqui et al. [9] further explored consumer behavior toward novel food trends, identifying factors such as education, taste, income, and exposure that influence acceptance. Baker et al. [10] conducted a scoping review to analyze global determinants affecting consumer acceptance of functional foods, providing insights into behavioral patterns and market trends.

2.3 Nutritional Value and By-Product Utilization

The utilization of food by-products has been widely studied for its economic and environmental benefits. Colletti et al. [5] examined soy-based by-products such as okara, highlighting its high nutritional value and potential applications in reducing environmental pollution. Similarly, Klerks et al. [12] reviewed the importance of whole grain cereals in infant nutrition, emphasizing health benefits and challenges related to processing, contamination, and consumer acceptance.

2.4 Food Safety and Health Impact Studies

Food safety and health-related impacts have been extensively investigated in recent research. Duarte et al. [6] analyzed the occurrence of ochratoxin A in food and biological samples, assessing exposure risks in the Portuguese population. Sousa et al. [7] studied the relationship between maternal consumption of ultra-processed foods and infant malnutrition, identifying significant associations with health outcomes. De Nucci et al. [8] further explored the impact of ultra-processed foods on dietary habits, particularly during the SARS-CoV-2 pandemic, highlighting shifts toward unhealthy consumption patterns.

2.5 Innovation, Sustainability, and Food Systems

Recent advancements focus on sustainable food systems and innovative approaches. Lombardo et al. [11] discussed global research trends in plant-based nutrition and sustainable food systems through an international conference platform. Grafia et al. [13] emphasized eco-friendly packaging solutions for functional foods, aligning with sustainability goals and consumer preferences. These studies highlight the integration of innovation, sustainability, and regulatory frameworks in modern food systems.

2.6 Research Gap

Although extensive research has been conducted on food processing, nutrition, and sustainability, several gaps remain. Many studies focus on individual aspects such as processing optimization, consumer behavior, or health impact, without integrating these components into a unified intelligent system. Additionally, there is limited research on leveraging advanced computational techniques such as machine learning for holistic food analysis and prediction. The proposed system addresses this gap by integrating data-driven approaches to improve decision-making, efficiency, and sustainability in food-related applications.

3. PROPOSED METHODOLOGY

The proposed system aims to automatically detect biscuit quality and defects using image-based machine learning and deep learning techniques. Initially, biscuit images are collected and preprocessed through resizing, normalization, and dataset splitting to prepare them for model training as shown in figure 2. Multiple classification models such as ETC, LDA, LGBM, and ResNet-CNN are trained to learn visual patterns related to biscuit quality and defects. The trained models are evaluated using performance metrics like accuracy, precision, recall, and F1-score to identify the most effective model. During prediction, the system analyzes a new biscuit image and classifies its quality category, while an AI-based analysis module further evaluates baking condition and surface defects. The system also supports batch prediction and Telegram bot integration to enable automated and real-time biscuit quality inspection.

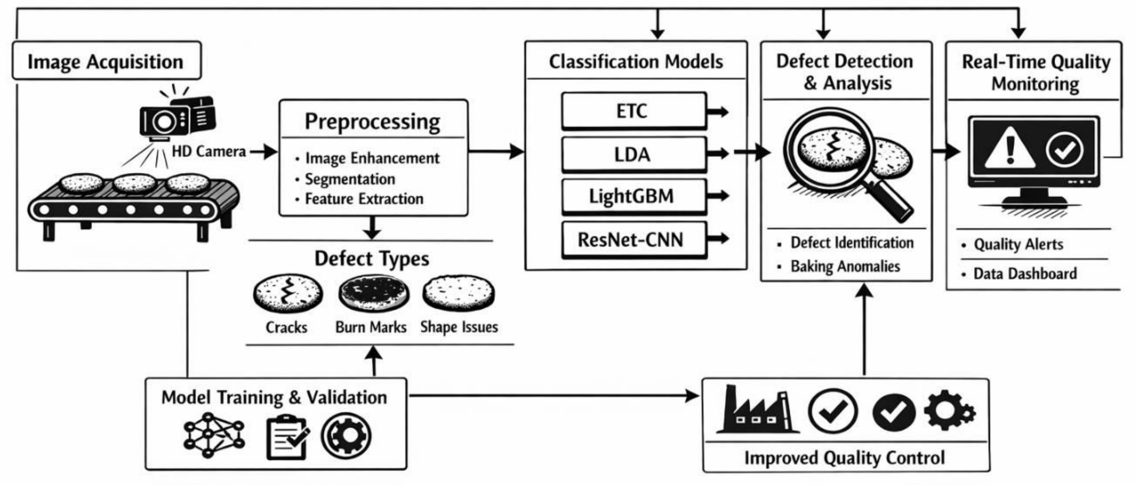

Fig. 2: Proposed system architecture of biscuit quality inspection and defect classification

1. Dataset Collection: The proposed system begins with collecting a dataset of biscuit or cookie images representing different quality categories. These images are organized into separate folders based on their class labels such as good, burnt, broken, or defective biscuits.

2. Dataset Upload and Initialization: The collected dataset is uploaded into the system through the graphical user interface. During this step, the system automatically identifies all category folders and stores the class labels for further processing.

3. Image Preprocessing: In the preprocessing stage, all images are resized to a fixed resolution of 64×64 pixels to maintain consistency. The images are normalized and converted into numerical arrays to prepare them for machine learning and deep learning models.

4. Data Splitting for Training and Testing: The processed dataset is divided into training and testing sets to evaluate model performance. Typically, 80% of the images are used for training the models while 20% are reserved for testing and validation.

5. Model Training Using Machine Learning Algorithms: Several machine learning algorithms such as ETC, LDA, and LGBM are trained using the extracted image features. These models learn patterns associated with different biscuit quality categories.

6. Deep Learning-Based Feature Learning: A ResNet-based CNN is implemented to automatically learn complex visual features from biscuit images. The CNN model processes images through convolutional layers, pooling layers, and dense layers to improve classification accuracy.

7. Performance Evaluation and Model Comparison: After training, each model is evaluated using metrics such as accuracy, precision, recall, and F1-score. Confusion matrix and ROC curves are generated to compare the performance of different models and identify the most effective classifier.

8. Biscuit Quality Prediction: Once the model is trained, the system allows users to upload a new biscuit image for prediction. The trained CNN model analyzes the image and predicts the quality category along with the confidence score.

9. AI-Based Quality Analysis (XAI Module): An explainable AI module analyzes the uploaded image to determine whether it is a cookie and evaluates its baking condition. The system also identifies possible defects such as cracks, burn marks, or uneven texture.

CNN

A CNN is a specialized type of neural network that can automatically learn spatial hierarchies of features from images. Unlike the ML models that required you to flatten the 64x64x3 image into a 12,288-pixel vector, the CNN processes the image as a 2D and 3D structure, preserving its spatial information as shown in below figure 3.

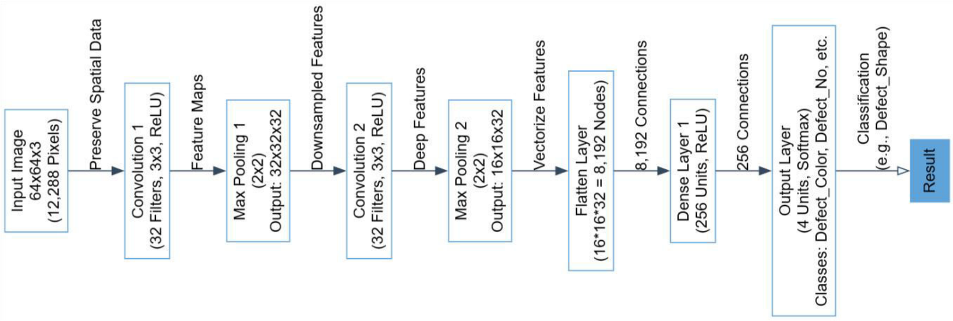

Figure 3: Internal workflow of CNN

1. Input and Convolution Layer (Feature Extraction): The 64 6400203 biscuit image is passed to the first Convolutional Layer. This layer uses 32 learnable filters (or kernels) of size (3 3). Each filter slides across the entire image, performing a dot product with the input pixels and generating a Feature Map. This process automatically extracts low-level features like edges, corners, and color blobs (relevant for detecting the defects). The ReLU activation function is applied to introduce non-linearity.

2. Pooling Layers: Immediately following the convolution, a Max-Pooling Layer of size (2 2) is applied. This layer takes the maximum value from each (2 2) region of the feature maps, effectively reducing the spatial dimensions (height and width) by half (from 64 64 to 32 32) while retaining the most important features. This also helps make the detection of a defect less sensitive to its exact location in the biscuit image.

3. Deeper Feature Learning: The process is repeated with a second set of Convolutional (32 filters) and Max-Pooling layers. This step enables the network to learn higher-level, more complex features by combining the simple features learned in the first layer. For instance, it might combine edges to recognize the overall shape of a defect or combine color blobs to identify a burn mark.

4. Flattening and Dense Layers: After the feature extraction blocks, the resulting 3D feature map is Flattened into a single vector. This vector is fed into a Dense (Fully Connected) Layer with 256 units. This layer combines all the learned high-level features and learns complex, non-linear relationships required for final classification.

5. Output Layer and Prediction: The final Dense Output Layer has units equal to the number of defect classes (4 in your case: Defect_Color, Defect_No, etc.) and uses the Softmax activation function. Softmax converts the network's output into a probability distribution over the four classes. The class with the highest probability is selected as the final predicted defect type for the biscuit.

4. Results description

Figure 4 shows confusion matrix demonstrates that the classification model performs well, with most samples correctly predicted along the diagonal, especially for No Defect and Shape Defect categories. However, minor misclassifications are observed between similar defect types such as Color Defect and No Defect. The ROC curve further confirms the model's strong performance, showing high True Positive Rates and low False Positive Rates across all classes. The AUC values ranging from 0.96 to

0.99 indicate excellent discrimination capability. Overall, the model achieves high accuracy and reliability in identifying different biscuit defect categories.

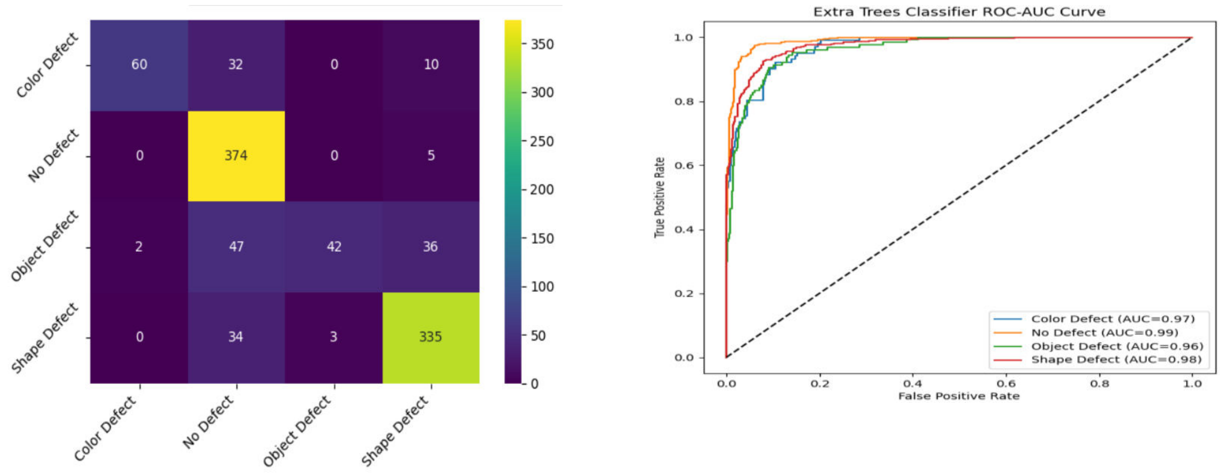

Figure 4: Confusion matrix and ROC curve obtained using ETC

The figure 5 shows confusion matrix of the LDA model shows that while some biscuit defect classes are correctly predicted, there are significant misclassifications between categories such as No Defect and Shape Defect. The diagonal values are lower compared to more advanced models, indicating weaker classification performance. The ROC-AUC curve further highlights this limitation, with AUC values around 0.50–0.60. Since the curves lie close to the diagonal, the model performs only slightly better than random guessing. Overall, the LDA classifier is less effective in accurately distinguishing between biscuit defect types.

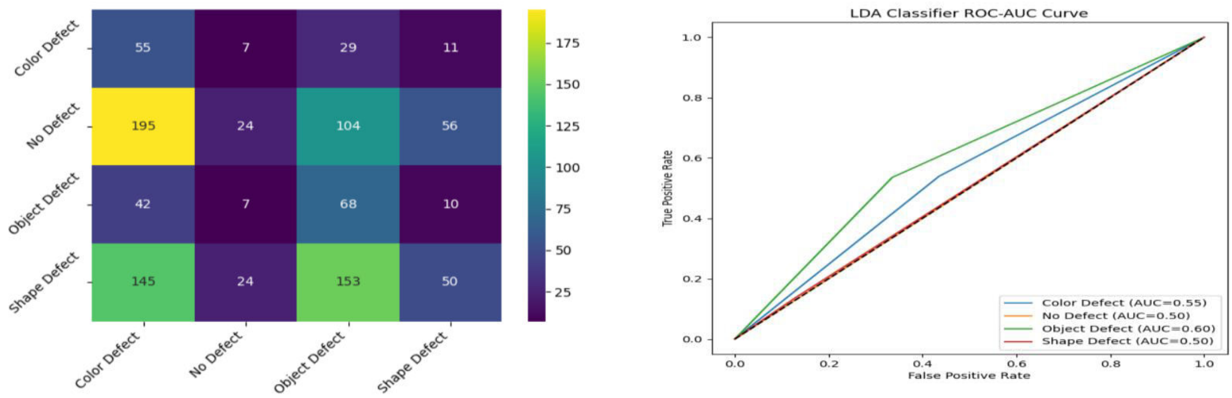

Figure 5: Confusion matrix and ROC curve obtained using LDA

The figure 6 The confusion matrix of the LGBM classifier shows strong performance, with most samples correctly classified along the diagonal, particularly for No Defect and Shape Defect categories. Only a few misclassifications occur between similar defect types, indicating high overall accuracy. The ROC–AUC curve further confirms this performance, with values around 0.98–0.99 for all classes. The curves lying near the top-left corner indicate high True Positive Rates and low False Positive Rates. Overall, the LGBM model demonstrates excellent reliability in distinguishing biscuit defect categories.

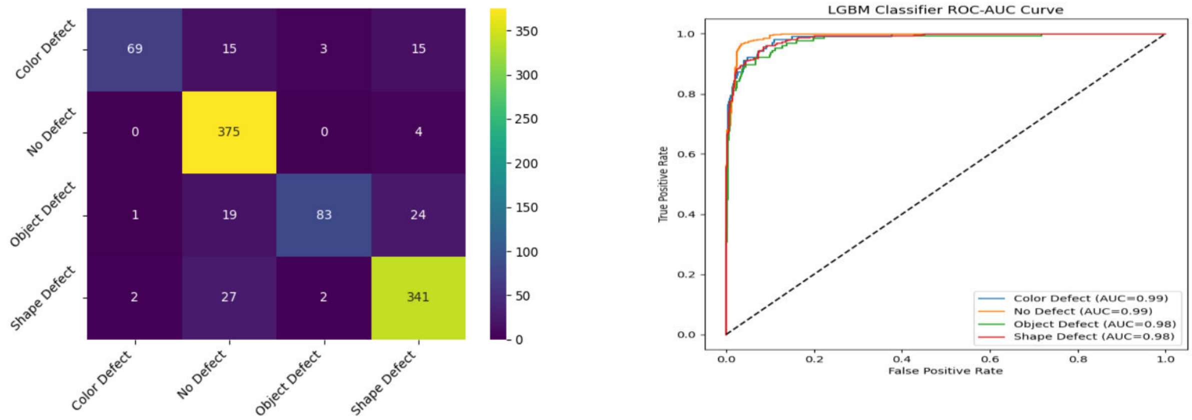

Figure 6: Obtained confusion matrix and ROC curve using LGBM Classifier

The figure 7 presents confusion matrix of the ResNet-based CNN model shows excellent performance, with most samples correctly classified along the diagonal for all defect categories. Only a minimal number of misclassifications are observed, indicating very high prediction accuracy. The ROC–AUC curve further confirms this, with all classes achieving an AUC of 1.00. The curves lie near the top-left corner, reflecting perfect discrimination between defect types. Overall, the CNN model outperforms other models in accurately detecting biscuit defects.

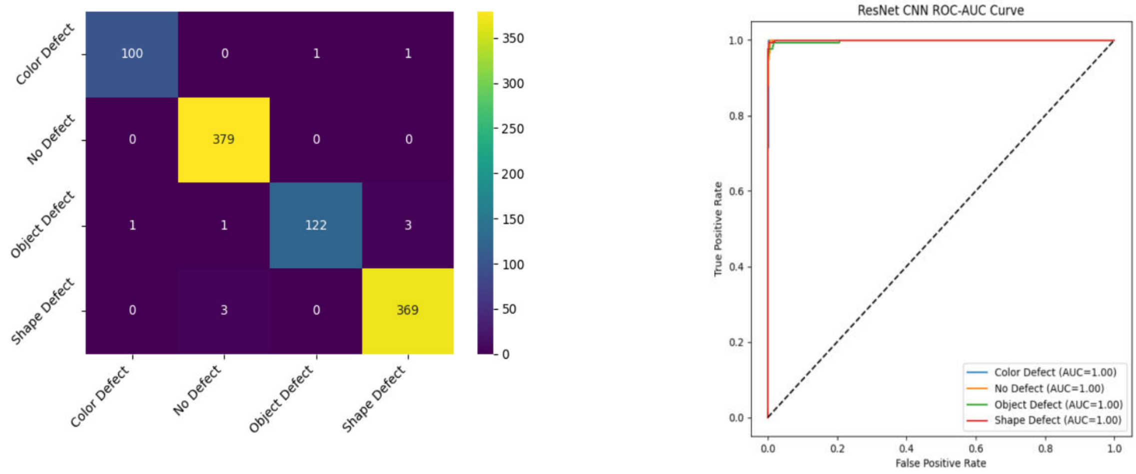

Figure 7: Obtained confusion matrix and ROC curve using proposed CNN Model

Table 1**:** Performance comparison for the ETC, LDA, LGBM and Proposed ResNet CNN model

Model	Accuracy	Precision	Recall	F1-Score
Extra Trees Classifier	0.8276	0.8842	0.7016	0.7419
LDA Classifier	0.2010	0.2747	0.3181	0.1990
LGBM Classifier	0.8857	0.9124	0.8090	0.8469
ResNet CNN	0.9898	0.9902	0.9832	0.9866

The table 1 compares the performance of four models based on accuracy, precision, recall, and F1-score. The ResNet CNN model achieves the highest performance across all metrics, indicating excellent classification capability. The LGBM classifier also performs well, showing strong accuracy and balanced precision-recall values. The Extra Trees classifier provides moderate performance, with good precision but relatively lower recall. In contrast, the LDA classifier performs poorly across all metrics, making it the least effective model for biscuit defect detection.

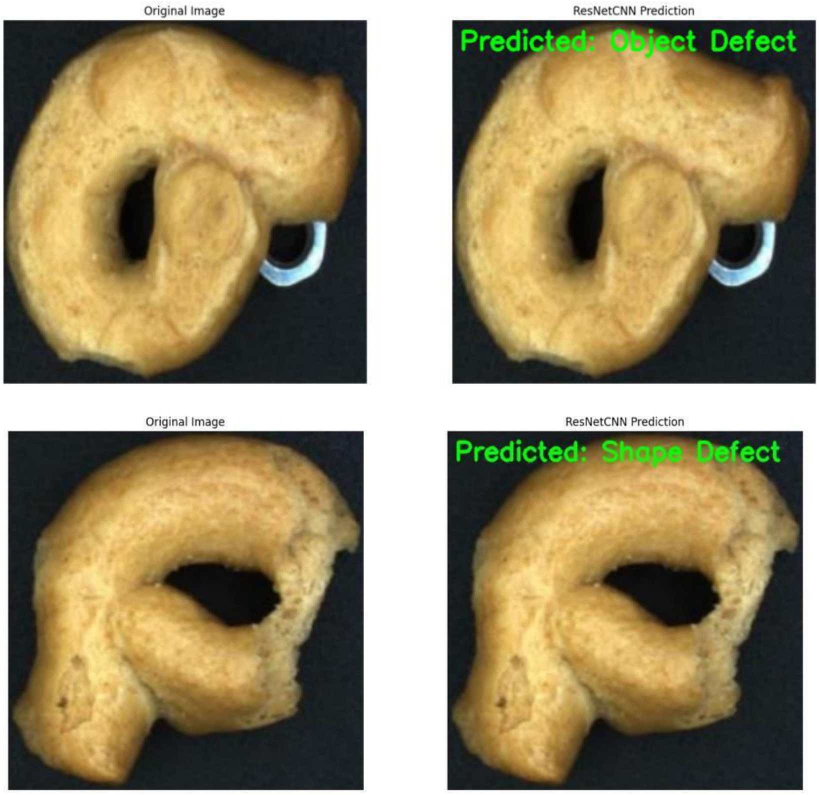

Figure 8: Prediction obtained on test images using proposed CNN

Figure 8 demonstrates the prediction results of the proposed ResNet CNN model for biscuit defect detection using different sample images. In each case, the left side shows the original biscuit image, while the right side displays the model's prediction with the detected defect label overlaid on the image. In the first two examples, the system correctly identifies the biscuit as having a Shape Defect, indicating irregular or distorted biscuit structure. In the third example, the model detects an Object Defect, where a foreign object or unwanted element appears near the biscuit. These results illustrate that the trained ResNet CNN model can effectively analyze biscuit images and accurately classify different types of defects, demonstrating its usefulness for automated quality inspection in food manufacturing processes.

Figure 9 illustrates the real-time biscuit quality prediction results generated through the Telegram bot integrated with the proposed ResNet CNN model. In the first example, a non-cookie image is sent to the bot, and the system correctly analyzes the input and responds that it is "Not a cookie image Detected: Other," demonstrating the bot's ability to distinguish irrelevant images. In the second example, when a biscuit image is provided, the bot successfully detects it as a cookie and performs quality analysis by reporting Quality: Good, Baking Condition: Properly baked, Surface Defects: None, along with the AI model prediction identifying a Color Defect. These results confirm that the Telegram bot can perform real-time biscuit detection and defect classification, allowing users to remotely analyze biscuit images and obtain automated quality assessment using the trained deep learning model.

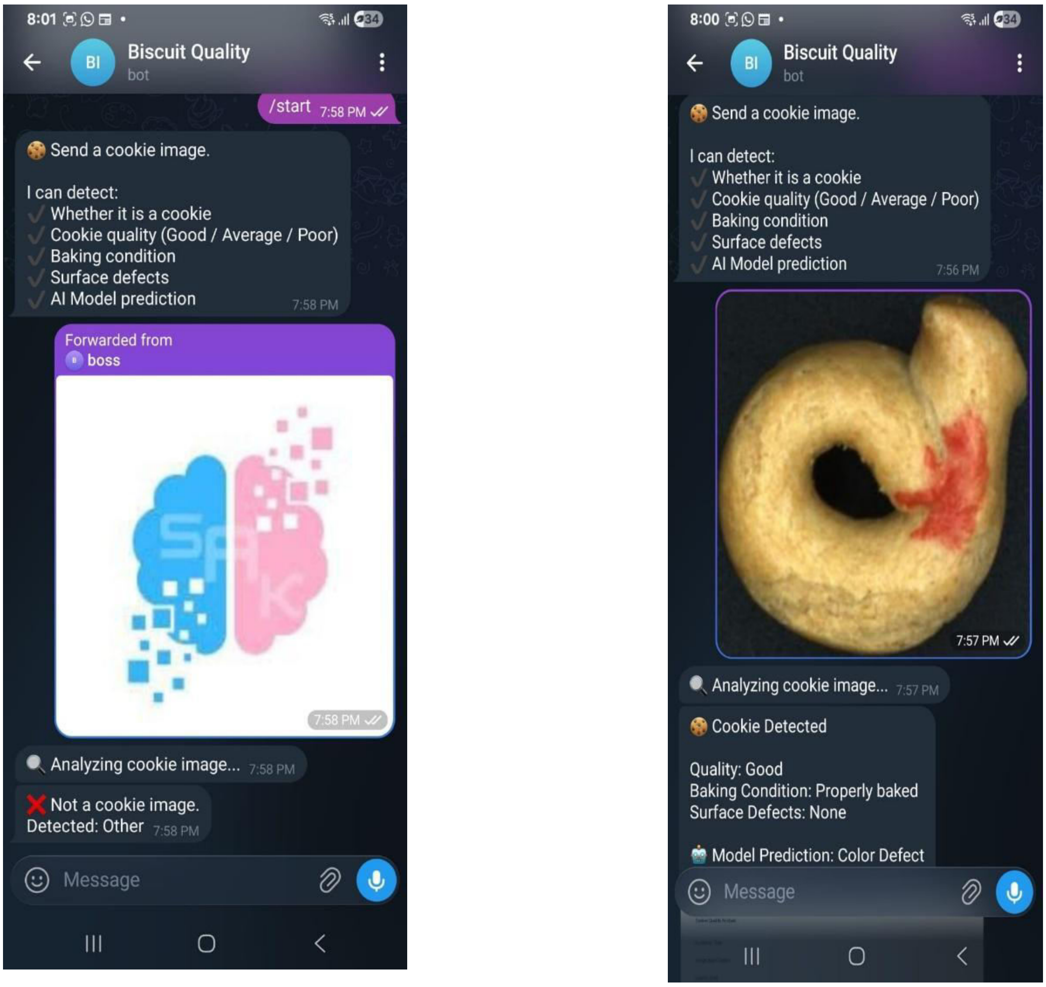

Figure 9: Real time prediction obtained using telegram bot

5. Conclusion

The AI-Based Biscuit Defect Detection System for Enhancing Food Industry Quality Control was successfully developed to automatically identify and classify biscuit defects using machine learning and deep learning techniques. The proposed system integrates image preprocessing, multiple classification models, and deep learning-based feature extraction to analyze biscuit images and determine defect categories such as Color Defect, No Defect, Object Defect, and Shape Defect. During implementation, the dataset was preprocessed through resizing, normalization, and conversion into numerical arrays to prepare it for model training. Several machine learning algorithms including ETC, LDA, and LGBM were implemented and evaluated alongside the proposed ResNet-based CNN model. Performance evaluation was carried out using metrics such as Accuracy, Precision, Recall, and F1-Score, along with visualization techniques including confusion matrices and ROC-AUC curves. The experimental results clearly demonstrated that the ResNet CNN model achieved the highest performance with an accuracy of approximately 98.98%, significantly outperforming traditional machine learning models by effectively learning complex visual patterns and features from biscuit images. The system also includes additional functionalities such as batch prediction, graphical result visualization, and Telegram bot integration, enabling real-time biscuit quality analysis and remote monitoring. The proposed system provides a reliable, automated, and efficient solution for biscuit defect detection, which can greatly assist food manufacturing industries in improving product quality inspection, reducing manual effort, and ensuring consistent product standards through intelligent image-based quality control.

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