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Research Paper

An End-to-End Deep Residual Learning Paradigm for Robust Visual Defect Detection and Quality Assessment in Baked Product Processing Systems

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ABSTRACT

In contemporary food manufacturing environments, the large-scale production of baked goods, necessitates highly reliable and efficient quality inspection mechanisms. Even minor visual imperfections, such as color inconsistencies, surface cracks, irregular shapes, or the presence of foreign objects, can result in significant product rejection, financial losses, and diminished consumer confidence. To overcome these challenges, this study presents an Automated Visual Inspection (AVI) framework designed for the classification and analysis of defects in baked goods using advanced computer vision and machine learning techniques. The proposed system processes image data collected from production lines and applies standardized preprocessing methods, including resizing, normalization, and enhancement, to ensure visual consistency. Feature extraction is performed using a pretrained Residual Network (ResNet), leveraging transfer learning to capture critical attributes such as texture, color, and structural patterns. These extracted features are then classified using Linear Discriminant Analysis (LDA), Light Gradient Boosting Machine (LGBM), and Extra Trees Classifier (ETC) to enable comparative evaluation. Furthermore, a ResNet-based Convolutional Neural Network (CNN) is implemented for end-to-end image classification. The system categorizes products into four classes: color defect, non-defect, object-related defect, and shape defect. A Graphical user interface (GUI) developed using Tkinter facilitates real-time image input and result visualization. Experimental findings demonstrate that the proposed framework enhances accuracy, consistency, and operational efficiency in industrial quality inspection.

Key words: Baked Goods Quality Assessment, Food Processing Automation, Industrial Quality Control, Automated Visual Inspection.

1. INTRODUCTION

Over the past decade, the global cookie and biscuit industry has shown consistent growth, driven by rising urbanization, changes in eating habits, and demand for packaged convenience foods. Emerging markets, especially in the Asia-Pacific region, experienced the fastest expansion, with countries like India showing a strong upward production trend from around 520 to 710 thousand metric tons between 2015 and 2024. In contrast, mature markets such as the United States demonstrated steady but moderate growth, moving from approximately 480 to 540 thousand metric tons over the same period. This widespread increase in consumption and production highlights the rapidly growing load on bakery manufacturing lines worldwide.

Fig 1. shows the growth of the India Cookies Market from 2019 to 2035. It presents a steady increase in market value every year, indicating rising demand for cookies across the country. In 2019, the market value was low, but it gradually increased over time. By 2024, the graph highlights a value of 1.9 billion USD, showing strong growth in just a few years. From 2025 onwards, the trend continues to move upward without any major drop. This shows that consumer interest, product variety, and market expansion are increasing. By 2035, the market reaches its highest value of 4.0 billion USD. This almost doubles the value compared to 2024.

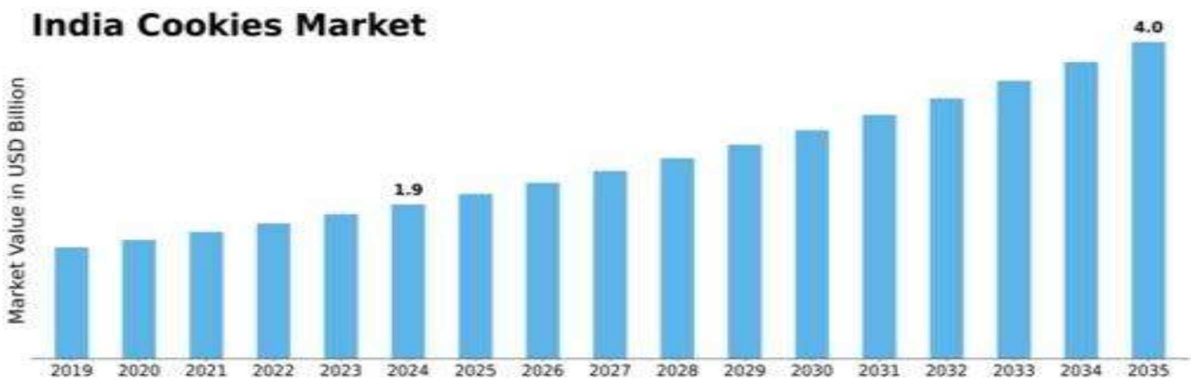

Fig.1. India Cookies Market (2019-2035).

The continuous rise suggests that cookie production will also increase heavily. At the same time, some developed markets like the United Kingdom experienced a gradual decline in production volumes, reflecting market saturation, shifting dietary preferences, and increased focus on premium, healthier products. Despite these variations, the global trend remains clear: rising overall production demands higher inspection accuracy, faster throughput, and more consistent quality control. These pressures make Automated Visual Inspection (AVI) systems increasingly essential, as they offer a scalable, accurate, and cost-efficient solution to meet modern industry standards while supporting the global demand–supply balance

Traditional quality control in biscuit manufacturing has predominantly depended on manual inspection, where workers visually examine products for defects such as cracks, discoloration, and shape irregularities. However, this method is inherently limited by human factors such as fatigue, inconsistency, and subjective judgment, which often lead to inaccurate assessments. Research in food engineering has highlighted that human-based inspection systems can exhibit notable error rates due to environmental conditions and cognitive variability. These limitations increase the risk of defective products reaching consumers and result in higher operational costs through waste, reprocessing, and potential brand damage. To address these challenges, the integration of artificial intelligence and computer vision has emerged as an effective alternative for automated quality control. The AI-driven biscuit defect detection system utilizes advanced image processing and deep learning models to perform precise and consistent inspections. By leveraging convolutional neural networks, the system can identify complex and subtle defect patterns that are difficult to detect manually. Additionally, it enables real-time, non-invasive, and high-speed inspection, making it highly suitable for large-scale food manufacturing environments while significantly improving efficiency and reliability.

2. LITERATURE SURVEY

2.1. Machine Learning and Imaging Techniques for Food Quality Assessment

Recent advancements in food quality evaluation have increasingly leveraged machine learning and imaging technologies. Lončar *et al.* [1] utilized Support Vector Machine (SVM) and Artificial Neural Network (ANN) models to predict multiple cookie quality parameters, demonstrating high predictive accuracy and enabling formulation optimization. Complementing this, Jelali *et al.* [2] explored microwave and terahertz imaging techniques for detecting internal defects and foreign objects in packaged food products, enabling non-destructive inspection in real-time production environments. Additionally, Kostal *et al.* [3] applied camera-based image processing systems within industrial assembly setups to detect inaccuracies and improve reliability. Together, these works highlight the growing importance of combining intelligent algorithms with imaging systems for automated and accurate food quality inspection.

2.2 Industrial Processing, Modeling, and Optimization in Food Systems

Several studies have focused on improving food processing efficiency and predictive modeling of food characteristics. Hu *et al.* [4] analyzed global potato-processing industries, emphasizing the role of automation and advanced quality-control mechanisms in developed countries. de Castro Cogle *et al.* [5] introduced a Bayesian hierarchical regression model to predict bioaccessibility in food products, achieving strong predictive performance and aiding formulation optimization.

Similarly, Păcală *et al.* [6] employed fuzzy logic modeling to optimize fermentation processes in food substrates. These approaches demonstrate how statistical and intelligent modeling techniques contribute to process optimization and improved food quality in industrial applications.

2.3 Consumer Behavior, Health Implications, and Recommendation Systems

Understanding consumer perception and health impacts is another critical dimension in food systems research. Cong *et al.* [7] reviewed the application of biometric techniques such as eye-tracking to capture implicit consumer responses, reducing bias in traditional surveys. Meanwhile, Brichacek *et al.* [8] and Capozzi *et al.* [9] investigated the effects of ultra-processed foods (UPFs), linking them to adverse health outcomes such as obesity and cardiovascular diseases, while also identifying research gaps in processing-related health impacts. Song *et al.* [10] highlighted limitations in conventional recommendation systems and emphasized the need for personalized approaches based on user sentiment. These studies collectively underline the intersection of consumer analytics, health awareness, and intelligent recommendation systems.

2.4 Sustainable Food Processing and Waste Valorization

Sustainability and resource optimization have gained significant attention in modern food research. Jaouhari *et al.* [11] emphasized circular economy principles, advocating the reuse of food waste and by-products to create value-added products. Castagna *et al.* [12] reviewed strategies such as extraction, bioconversion, and composite production for agricultural waste valorization, highlighting both benefits and challenges. Rebollo-Hernanz *et al.* [13] proposed a systematic framework for developing functional food ingredients from by-products, integrating characterization, formulation, and validation stages. Additionally, Colletti *et al.* [14] explored the utilization of soy by-products like okara as nutritionally rich and sustainable food ingredients. These contributions demonstrate the potential of sustainable technologies in reducing waste and enhancing food system efficiency.

2.4 Food Structure, Processing Dynamics, and Material Behavior

Fundamental research on food structure and processing dynamics provides insights into material behavior and quality characteristics. Purlis *et al.* [15] examined the role of water and structural transformations during oral processing, emphasizing its impact on mechanical properties and food behavior. Such studies are essential for developing accurate predictive models and improving the design of food products with desired texture and quality attributes.

3. PROPOSED METHODOLOGY

The proposed system presents an Automated Visual Inspection (AVI)–based quality inspection classification framework for baked goods, designed to accurately identify and categorize defects related to color, shape, object presence, and defect-free samples. The system leverages deep learning–based feature extraction using a ResNet architecture combined with traditional and ensemble machine learning classifiers to ensure robust and reliable defect classification. By integrating image preprocessing, feature learning, comparative model evaluation, and a user-friendly Tkinter-based interface, the system provides an end-to-end solution for automated quality control in baked goods manufacturing. The final output classifies each product into predefined defect categories, supporting faster inspection, reduced human error, and consistent quality assessment as shown in fig 2

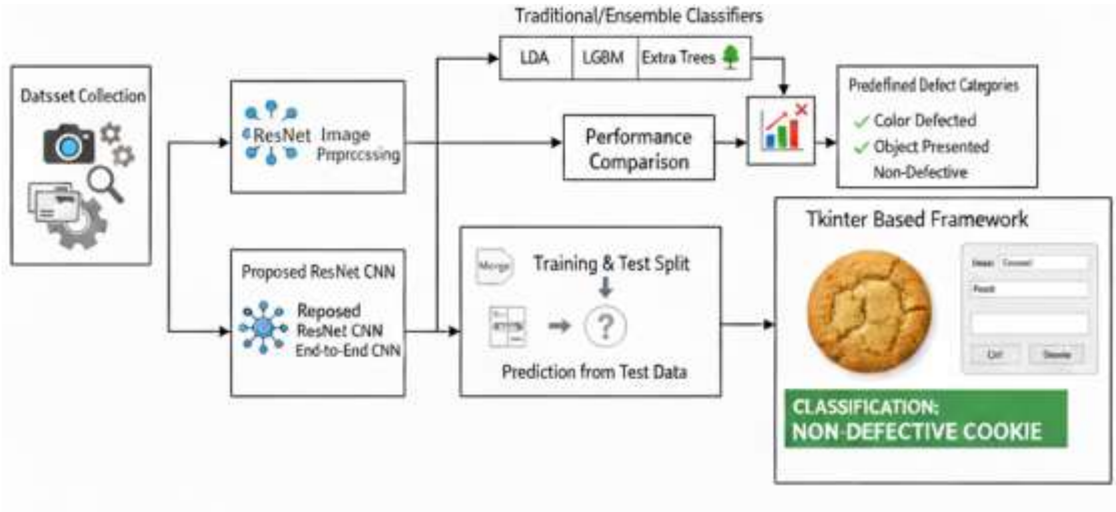

Fig. 2. Proposed system architecture of biscuit quality inspection and defect classification

The proposed system begins with the collection of a labeled image dataset of baked goods, categorized into four classes: color-defected cookies, non-defective cookies, object-present cookies, and shape-defected cookies, ensuring diversity under both controlled and real production conditions. The images undergo preprocessing steps including resizing, noise reduction, normalization, illumination correction, and color space enhancement to improve consistency and defect visibility. These refined images are then passed through a pretrained ResNet model using transfer learning, where deep feature vectors are extracted by removing the fully connected layers, capturing both low-level textures and high-level defect patterns. The extracted features are subsequently divided into training and testing sets using a fixed split ratio with proper shuffling to ensure unbiased evaluation and avoid class imbalance effects.

For classification, multiple models are implemented and compared. LDA serves as a baseline to evaluate linear separability and dimensionality reduction effectiveness, while LGBM captures complex non-linear relationships through optimized ensemble learning, and the ETC enhances robustness using randomized decision trees to reduce overfitting. In contrast, the proposed ResNet-based CNN performs end-to-end defect classification by directly learning from images through fine-tuning, offering improved accuracy and robustness. All models are evaluated using performance metrics such as accuracy, precision, recall, and F1-score, followed by prediction on unseen test data to validate real-world applicability. Finally, the system is integrated into a Tkinter-based graphical user interface, allowing users to upload images and receive instant defect classification results, thereby enabling a practical and user-friendly deployment of the automated visual inspection system.

3.1 ResNet CNN

The proposed method begins by forming application-specific inputs using MLP-derived features extracted from industrial image data, which are reshaped to suit the ResNet CNN input. These features pass through the initial convolution layer and successive residual blocks of the ResNet CNN architecture, as illustrated in Fig. 3. where identity connections enable effective refinement of structural and texture-related patterns while preserving essential information. Hierarchical down sampling between residual stages enhances robustness by focusing on discriminative features, and the deeper layers learn high-level semantic representations relevant to industry group classification. Finally, global average pooling aggregates the refined feature maps into a compact feature vector that represents the overall industrial characteristics for reliable classification.

The proposed method begins with application-specific input formation, where features extracted from an MLP model represent high-level visual patterns such as structural layouts, texture distributions, and material characteristics of industrial image data. These MLP-derived features are carefully organized and reshaped to match the input requirements of a ResNet-based CNN, enabling seamless integration into convolutional processing. The reshaped inputs are then passed through the initial convolutional layer, where feature alignment is performed by projecting abstract feature vectors into structured feature maps. This transformation allows the model to capture localized relationships and interactions among feature components, effectively converting non-spatial representations into spatially meaningful patterns suitable for deep learning.

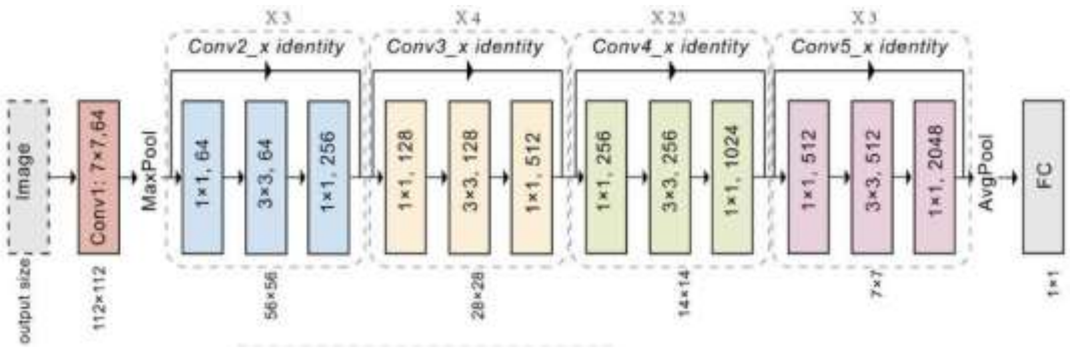

Fig. 3. ResNet Using CNN architecture

Following this, the feature maps are processed through multiple residual blocks, where each block incrementally refines the representations while preserving essential information through identity connections. Early layers focus on capturing coarse structural patterns, while deeper layers learn complex and abstract industry-specific characteristics. Hierarchical refinement is further achieved through downsampling operations such as pooling and stride-based convolutions, which reduce spatial dimensions while retaining the most discriminative features. In the final stages, the network extracts high-level semantic representations that encode intricate feature interactions critical for classification. These refined feature maps are then condensed using global average pooling, resulting in a compact and fixed-length feature vector that effectively summarizes the most important information for accurate industry group classification.

4. RESULTS DESCRIPTION

Fig 4. shows the GUI developed for the research work titled Automated Visual Inspection Pipelines for Baked Goods: Quality Control and Defect Taxonomy. The interface is designed to provide a complete and sequential workflow for automated defect inspection in baked goods, where the left-side panel presents control buttons for major stages such as dataset uploading, image processing, dataset splitting, training of Extra Trees, LDA, LGBM, and ResNet-CNN models, as well as options for test image prediction and graphical analysis. The central panel serves as the visualization area for displaying processed images, intermediate results, and system outputs during execution, while the background imagery of an industrial conveyor inspection setup with baked cookies represents the real-world manufacturing environment targeted by the system.

Fig 4. GUI interface for dataset upload for baked goods quality prediction

The figure 5 represents the confusion matrix obtained after training the LGBM classifier in the biscuit defect detection system. The matrix compares the actual defect categories with the predicted classes for four biscuit conditions: Color Defect, No Defect, Object Defect, and Shape Defect. The diagonal values indicate correctly classified samples, such as 372 No Defect and 345 Shape Defect images, showing strong prediction performance for these classes. A few off-diagonal values represent misclassifications between similar defect types, such as Object Defect being predicted as Shape Defect or No Defect. The matrix demonstrates that the LGBM model achieves good classification accuracy with relatively fewer prediction errors across the defect categories.

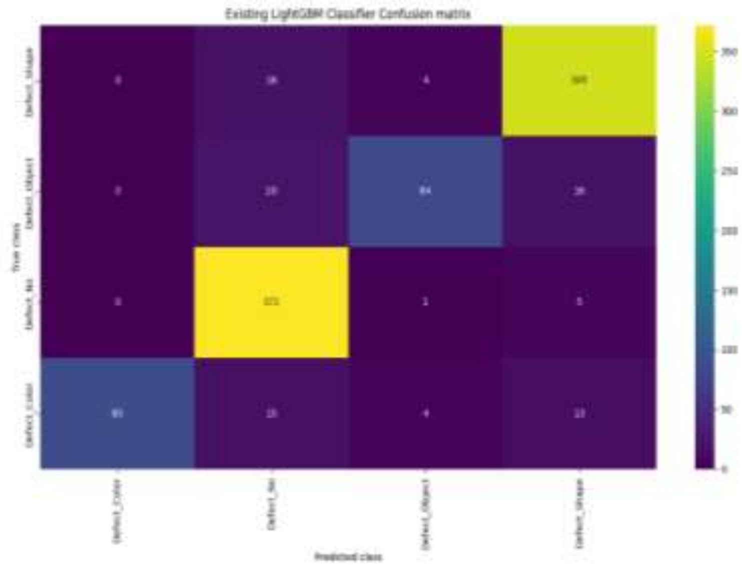

Fig 5. Illustration of confusion matrix using LGBM Classifier

Fig 6. shows the ROC–AUC curve of the LGBM classifier used in the biscuit defect detection system. The graph illustrates the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) for each biscuit defect class: Color Defect, No Defect, Object Defect, and Shape Defect. The AUC values are very high (around 0.98–0.99) for all classes, indicating that the LGBM model has excellent capability to distinguish between different biscuit defect categories. The curves are positioned very close to the top-left corner of the graph, which signifies strong classification performance with high detection accuracy and a very low false positive rate.

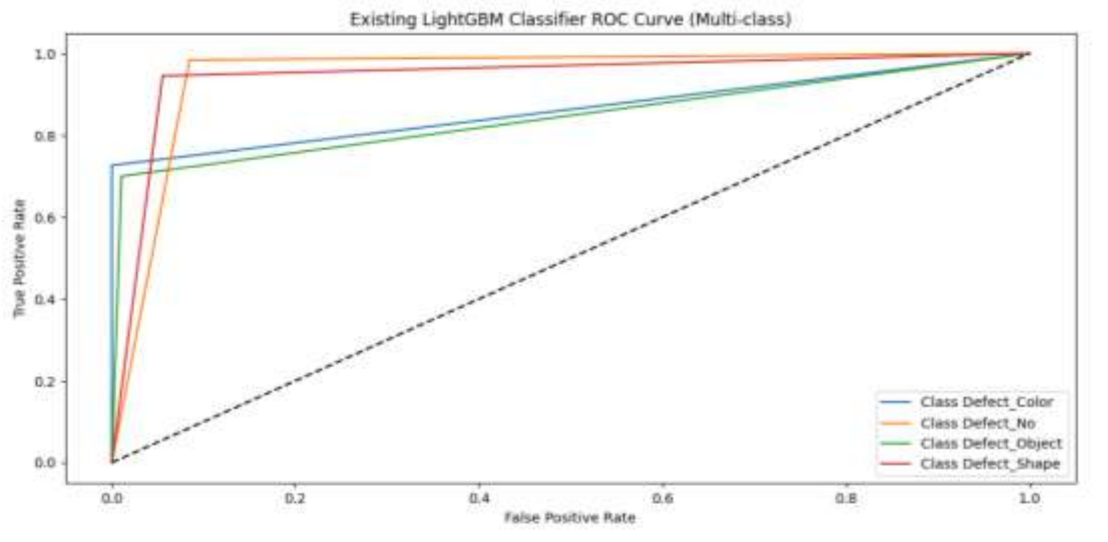

Fig 6. ROC obtained using LGBM Classifier

The figure 7. presents the confusion matrix of the ResNet-based CNN model used for biscuit defect classification. It compares the actual biscuit defect classes with the predicted classes for the categories Color Defect, No Defect, Object Defect, and Shape Defect. Most values appear along the diagonal of the matrix, such as 90 Color Defect, 375 No Defect, 95 Object Defect, and 376 Shape Defect, indicating that the CNN model correctly classifies the majority of the samples. Only a very small number of misclassifications are observed, demonstrating that the CNN model achieves very high prediction accuracy and performs better than the traditional machine learning models in detecting biscuit defects.

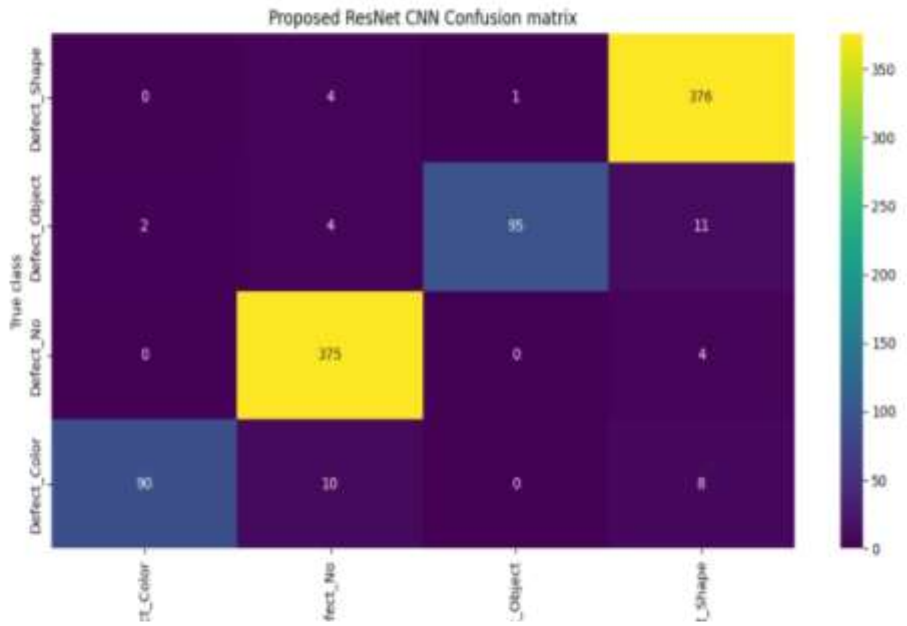

Fig 7. Illustration of confusion matrix using proposed CNN Model

The fig 8. illustrates the ROC–AUC curve of the ResNet-based CNN model used in the biscuit defect detection system. The graph shows the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) for each biscuit defect category: Color Defect, No Defect, Object Defect, and Shape Defect. All classes achieve an AUC value of 1.00, indicating perfect classification performance by the CNN model. The ROC curves lie very close to the top-left corner, demonstrating that the model can accurately distinguish between different biscuit defect types with extremely high sensitivity and a very low false positive rate

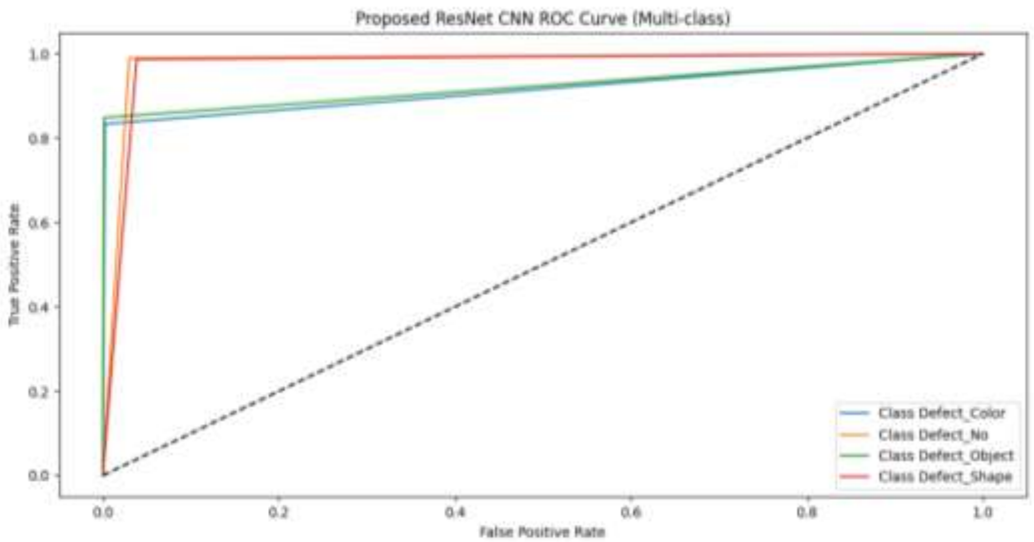

Fig 8. ROC Obtained using proposed CNN Model

Fig 9. shows the training and validation accuracy and loss curves of the proposed ResNet CNN model across successive training epochs. As illustrated in Figure 9.3.10, the training accuracy increases steadily from approximately 0.68 in the initial epoch to about 0.97 in the final epoch, while the validation accuracy follows a similar trend, rising from around 0.85 to nearly 0.96, indicating stable and consistent learning behavior. Correspondingly, the training loss decreases sharply from about 0.75 to nearly 0.11, and the validation loss reduces from approximately 0.45 to around 0.18, demonstrating effective minimization of classification error. The close alignment between training and validation curves suggests that the model achieves good generalization without significant overfitting.

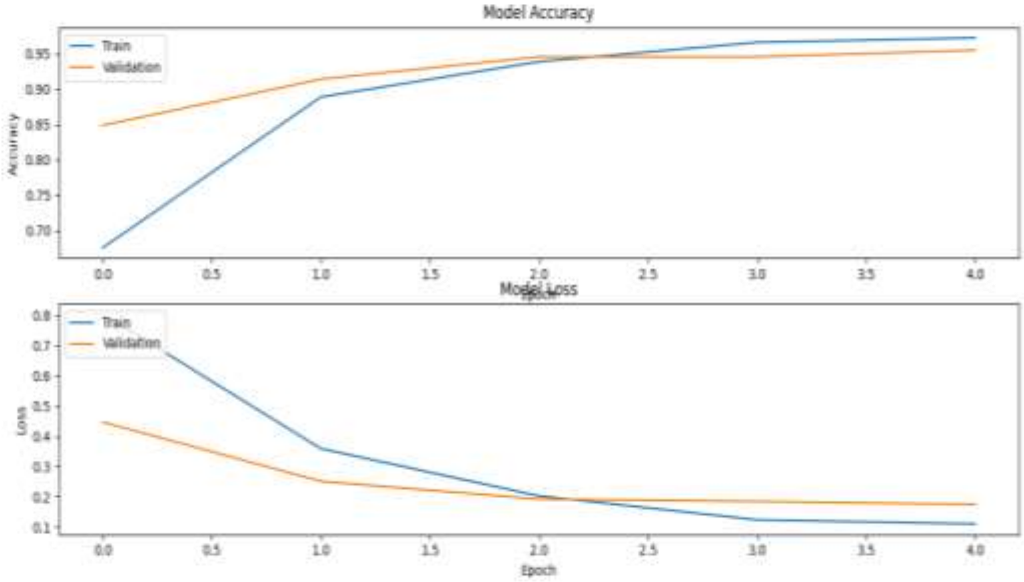

Fig 9. Accuracy and Loss graph obtained using proposed ResNet CNN model.

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 presents the performance comparison of different classification models used in the biscuit defect detection system, including ETC, LDA Classifier, LGBM Classifier, and the proposed ResNet-based CNN model. The comparison is based on evaluation metrics such as Accuracy, Precision, Recall, and F1-Score. The ETC achieves an accuracy of 0.8276, with precision 0.8842, recall 0.7016, and F1-score 0.7419, showing moderate performance in identifying biscuit defects. The LDA Classifier performs significantly worse with an accuracy of 0.2010, indicating that linear classification methods are not suitable for complex image-based defect detection tasks. The LGBM Classifier improves the performance with an accuracy of 0.8857, precision 0.9124, recall 0.8090, and F1-score 0.8469, demonstrating strong predictive capability compared to traditional models. However, the ResNet CNN model clearly outperforms all other classifiers, achieving the highest accuracy of

0.9898, precision 0.9902, recall 0.9832, and F1-score 0.9866, indicating excellent capability in learning complex visual features from biscuit images and accurately classifying defect categories. These results confirm that the deep learning-based ResNet CNN model provides the most reliable and accurate solution for automated biscuit quality detection compared to conventional machine learning approaches.

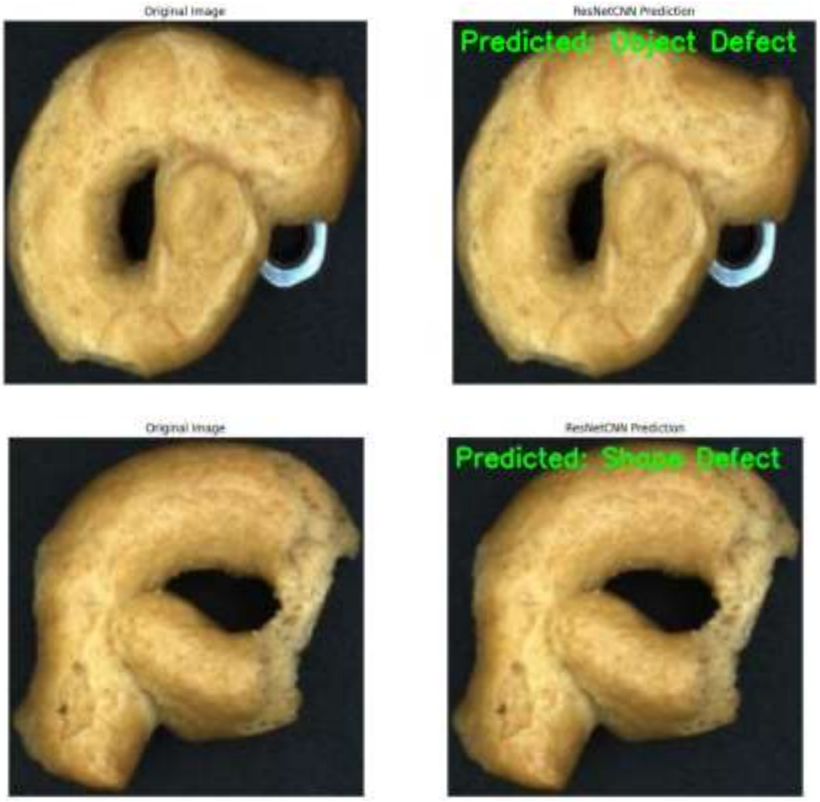

Figure 10. Prediction obtained on test images using proposed CNN

Figure 10. 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.

5. CONCLUSION

The research clearly highlights the effectiveness of deep learning–based automated visual inspection for quality assessment in baked goods. A comparative evaluation of conventional and ensemble classifiers reveals a gradual improvement in performance. The ETC demonstrated relatively low discriminative capability, achieving an accuracy of 63.06%. LDA showed moderate improvement with an accuracy of 67.45%, indicating better class separation than ETC. The LGBM significantly enhanced classification performance, achieving 90.41% accuracy, 92.32% precision, and 83.89% recall. However, despite this improvement, these traditional and ensemble approaches still exhibited misclassification issues, particularly among visually similar defect categories such as color-defected and object-present cookies. In contrast, the proposed ResNet CNN) outperformed all other models, achieving an accuracy of 95.51%, precision of 96.61%, recall of 91.44%, and an F1-score of 93.72%. Analysis of the confusion matrix and ROC curves demonstrates that the model provides balanced and consistent predictions across all defect classes with minimal errors. Furthermore, the training and validation performance trends confirm stable convergence and strong generalization capability. The findings validate that deep residual feature learning is highly effective for detecting complex visual defects, making it a reliable and scalable solution for automated quality inspection in industrial baked goods production.

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