AI-Driven Biscuit Defect Detection System for Advanced Quality Assurance in Food Manufacturing

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ABSTRACT

The quality assurance of biscuits in modern food manufacturing environments plays a vital role in maintaining product consistency, consumer satisfaction, and brand reliability. Conventional manual inspection methods have been widely used; however, they are often inefficient, time-consuming, and susceptible to human errors, especially when identifying minor or subtle defects. To overcome these limitations, an AI-driven biscuit defect detection system was developed to automate the inspection process and enhance quality control standards within the industry. The system utilized advanced image processing techniques combined with artificial intelligence to analyze biscuit images and classify them into categories such as color defects, shape defects, object contamination, and defect-free samples. Initially, the dataset was pre-processed through resizing, normalization, and transformation into numerical formats suitable for model training. Various machine learning models, including Extra Trees Classifier (ETC), Linear Discriminant Analysis (LDA), and Light Gradient Boosting Machine (LGBM), were implemented and evaluated. In addition, a ResNet-based Convolutional Neural Network (CNN) was proposed to automatically extract deep and complex visual features from the images. The performance of all models was assessed using evaluation metrics such as accuracy, precision, recall, and F1-score, along with visualization tools like confusion matrices and ROC-AUC curves. Experimental findings indicated that the ResNet CNN model significantly outperformed traditional approaches, achieving an accuracy of approximately 98.98%. Furthermore, the system was integrated with a user-friendly graphical interface that facilitated dataset handling, model training, real-time prediction, and result visualization. Additional features, including batch processing and remote monitoring through a Telegram bot, enhanced system usability.

Keywords: Biscuit defect detection, quality assurance, image processing, machine learning, Deep learning, defect classification, food manufacturing.

1.INTRODUCTION

Quality assurance in modern food manufacturing is essential for maintaining product consistency and strengthening consumer trust. However, traditional inspection methods for biscuit quality are often manual, time-consuming, and susceptible to human error, creating a strong need for intelligent automation. The emergence of artificial intelligence and computer vision technologies has enabled the development of advanced inspection systems that improve both accuracy and efficiency. As shown as figure 1 In conventional biscuit production lines, quality assessment is typically performed through human visual inspection or basic rule-based optical systems. Manual inspection, while adaptable, is labor-intensive and highly dependent on the inspector's attention and experience, often resulting in inconsistencies and overlooked defects. Similarly, traditional optical systems rely on fixed thresholds for parameters such as color and shape, making them less effective in identifying complex or previously unseen defects. To address these challenges, the AI-driven biscuit defect detection system utilizes deep learning and machine learning models to analyze visual features with greater precision and adaptability. The system is capable of identifying multiple defect categories, including color variations, shape irregularities, and surface imperfections, without requiring frequent recalibration. Experimental observations indicate that defect detection accuracy significantly improves when using deep learning models, particularly under varying production conditions. This demonstrates the effectiveness of intelligent, automated solutions in delivering reliable, scalable, and high-precision quality control in biscuit manufacturing environments.

Figure 1: Quality inspection of Biscuits.

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

Lončar, B et al. [1] focused on predicting and optimizing the quality parameters of cookies enriched with dehydrated peach through the application of Support Vector Machine (SVM) and Artificial Neural Network (ANN) models. The purpose of the study is to employ advanced machine learning techniques to understand the intricate relationships between input parameters, such as the presence of dehydrated peach and treatment methods (lyophilization and lyophilization with osmotic pretreatment), and output variables representing various quality aspects of cookies. For each of the 32 outputs, including the parameters of the basic chemical compositions of the cookie samples, selected mineral contents, moisture contents, baking characteristics, color properties, sensorial attributes, and antioxidant properties, separate models were constructed using SVMs and ANNs. Results showcase the efficiency of ANN models in predicting a diverse set of quality parameters with r^2 up to 1.000, with SVM models exhibiting slightly higher coefficients of determination for specific variables with r^2 reaching 0.981.

Jelali, B et al. [2] dealt with the exploitation of microwave/terahertz imaging technology for food quality control and assessment. In particular, the work aims at reviewing the latest developments regarding the detection of internal quality parameters, such as foreign bodies, i.e., plastic, glass, and wood substances/fragments, as well as checking the completeness of the packaged food under consideration. Emphasis is placed on the (inline) inspection of wrapped/packaged food, such as chocolates, cookies, pastries, cakes, and similar confectionery products, moving along production conveyor belts. Kostal, B et al. [3] proposed experiments are realized in the flexible manufacturing system ICIM 3000 (FESTO, Germany), and its assembly system, located at the Institute of production technologies, Faculty of Material Sciences and Technologies, Slovak University of Technology. The assembly system is the final product assembled, and this process consists of five components. Unwanted inaccuracies in the assembly process of the elements, such as the insertion of thermometers and hygrometers into the base plate, usually arise. Based on these inaccuracies, we realize some experiments by the camera system SBOC-Q-R3-WB. This deals with the method of image processing. The camera system parameters are set-up.

Hu, B et al. [4] provided a comprehensive comparison of the potato-processing industries in China and major global producers. The global potato-processing market was valued at USD 40.97 billion in 2023 and is researched to reach USD 60.08 billion by 2031, with significant variations in production and consumption patterns across countries. As the world's largest potato producer, China processes approximately 15% of its total potato output, whereas India, the second-largest producer, processes only about 7%. In contrast, developed countries such as the United States, Canada, and leading European nations including Germany, the Netherlands, France, and Belgium demonstrate significantly higher levels of processing, underpinned by advanced technologies, automation, and efficient quality-control systems. de Castro Cogle, B et al. [5] developed a mathematical model to predict curcuminoid's bioaccessibility in biscuits and custard based on different fibre type formulations. Bioaccessibilities for curcumin-enriched custards and biscuits were obtained through in vitro digestion, and physicochemical food properties were characterised. A strong correlation between macronutrient concentration and bioaccessibility was observed ($p = 0.89$) and chosen as a main explanatory variable in a Bayesian hierarchical linear regression model. Additionally, the patterns of food matrix effects on bioaccessibility were not the same in custards as in biscuits; for example, the hemicellulose content had a moderately strong positive correlation to bioaccessibility in biscuits ($p = 0.66$) which was non-significant in custards ($p = 0.12$).

Cong, B et al. [6] proposed challenge in social marketing studies is the cognitive biases in consumers' conscious and self-reported responses. To address this concern, biometric techniques have been developed to obtain data from consumers' implicit and non-verbal responses. A systematic literature review was conducted to explore biometric applications' role in agri-food marketing to provide an integrated overview of this topic. A total of 55 original research articles and four review articles were identified, classified, and reviewed. It was found that there is a steady growth in the number of studies applying biometric approaches, with eye-tracking being the dominant method used to investigate consumers' perceptions in the last decade. Brichacek, B et al. [7] provided Ultra-processed foods (UPFs) are foods that are industrially processed and are often pre-packaged, convenient, energy-dense, and nutrient-poor. UPFs are widespread in the current Western diet and their proposed contribution to non-communicable diseases such as obesity and cardiovascular disease is supported by numerous studies. UPFs are hypothesized to affect the body in multiple ways, including by inducing changes in the gut microbiome.

Capozzi et al. [8] proposed the narrative synthesis and scientific reappraisal of available evidence aims to critically evaluate UPF-related scientific literature on diet and disease and identify possible research gaps or biases in the interpretation of data emphasize the innovative potential of various processing technologies that can lead to modifications of the food matrix with beneficial health effects highlight the possible links between processing, sustainability and circular economy through the valorisation of by-products and delineate the conceptual parameters of new paradigms in food evaluation and classification systems. Rebollo-Hernanz et al. [9] proposed a stepwise approach for the development of functional food ingredients and nutraceuticals from coffee by-products, covering the identification of needs, comprehensive characterization, in vitro and in vivo research, unraveling the mechanism of action, food and nutraceutical formulation, sensory analysis, shelf-life stability, scale-up, randomized control trials, and biostatistics and bioinformatic integration.

Jaouhari et al. [10] explored that according to the United Nations, approximately one-third of the food produced for human consumption is wasted. The actual linear "Take-Make-Dispose" model is nowadays obsolete and uneconomical for societies and the environment, while circular thinking in production systems and its effective adoption offers new opportunities and benefits. Following the "Waste Framework Directive" (2008/98/CE), the European Green Deal, and the actual Circular Economy Action Plan, when prevention is not possible, recovering an unavoidable food waste as a by-product represents a most promising pathway. Using last year's by-products, which are rich in nutrients and bioactive compounds, such as dietary fiber, polyphenols, and peptides, offer a wake-up call to the nutraceutical and cosmetic industry to invest and develop value-added products generated from food waste ingredients. Castagna et al. [11] reviews identified extraction, composite production, and bioconversion as the main strategies for valorizing agricultural by-products and waste. The advantages of these approaches as well as efficiency gains through digitalization are discussed, along with their potential applications in the Mediterranean region to support new research activities and bioeconomic initiatives. Moreover, the review highlights the challenges and disadvantages associated with waste valorization, providing a critical comparison of different studies to offer a comprehensive perspective on the topic.

Păcală et al. [12] studied fuzzy logic modeling (FLM) was used to optimize the lactic fermentation process of several buckwheat (Fagopyrum esculentum)-based substrates (B-bSs), which were bio-prospected for the development of pseudocereal-based fermented foodstuffs. The experimental methodology involved obtaining B-bSs, either green or roasted, under various milling conditions and subjecting them to two different types of thermal treatment. Purlis et al. [13] proposed food is broken down during oral processing. Such phenomena are the result of complex and dynamic relationships between composition and structure of foods, and driving forces established by processes and operating conditions. In particular, water plays a key role as a plasticizer, strongly influencing the state of amorphous materials via the glass transition and, thus, their mechanical properties. Therefore, it is important to improve the understanding about these complex phenomena and to develop useful prediction tools. For this aim, different modelling approaches have been applied in the food engineering field. Song et al. [14] proposed traditional recommendation systems to make recommendations based on the popularity of viral foods or user ratings. However, because of the different sentimental levels of users, deviations occur and it is difficult to meet the user's specific needs.

Colletti et al. [15] proposed increased awareness of the health benefits associated with consuming soy-based foods, knowledge of milk-related allergies and a move towards more sustainable food production have led to an increase in the number of available soy-based products. The biggest producers in the world, the USA, South America and China, are from the Pacific region. This enormous production is accompanied by the accumulation of related by-products, in particular, a substance that is known as okara. Okara is a paste that is rich in fibre (50%), protein (25%), fat (10%), vitamins and trace elements. Its proper use would lead to economic advantages and a reduction in the potential for polluting the environment. Its high fibre content and low production costs mean that it could also be used as a dietary supplement to prevent diabetes, obesity and hyperlipidaemia. Chemical or enzymatic treatment, fermentation, extrusion, high pressure and micronisation can all increase the soluble fibre content, and thus improve nutritional quality and processing properties.

3. PROPOSED SYSTEM

The AI-Driven Biscuit Defect Detection System for Advanced Quality Assurance in Food Manufacturing (AI-DBDDSAQA) was developed to automate and enhance the inspection of biscuit quality using advanced image-based machine learning and deep learning techniques as shown in the figure 2. Initially, biscuit images were collected and preprocessed through resizing, normalization, and dataset splitting to ensure efficient training and evaluation. Multiple models, including Extra Trees Classifier (ETC), Linear Discriminant Analysis (LDA), and Light Gradient Boosting Machine (LGBM), were implemented alongside a ResNet-based Convolutional Neural Network (CNN) to effectively learn and identify visual defect patterns. The models were evaluated using performance metrics such as accuracy, precision, recall, and F1-score to determine the most reliable approach. During prediction, the system analyzed new images and classified biscuits into quality categories while also assessing baking conditions and surface defects through an AI-based analysis module. Additionally, the system supported batch processing to handle multiple images simultaneously, improving operational efficiency. Integration with a Telegram bot enabled remote and real-time monitoring of biscuit quality. The system provided an intelligent, scalable, and efficient solution for improving consistency and reliability in food manufacturing quality control.

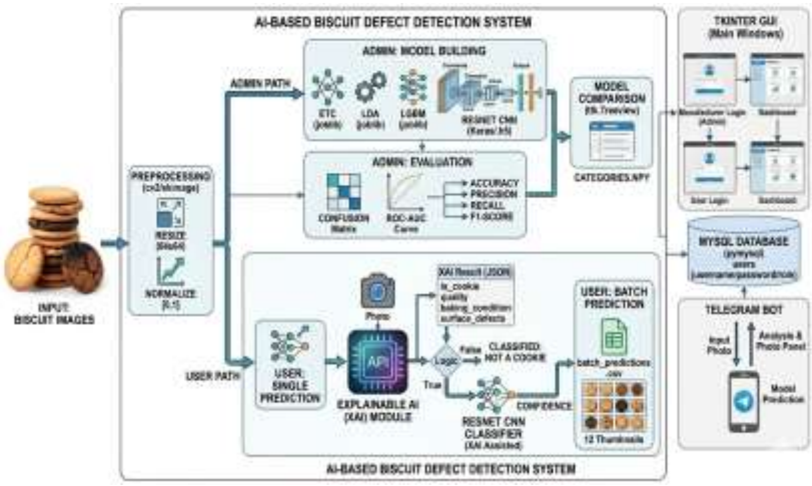

Figure 2: Proposed system architecture of biscuit quality inspection and defect classification

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.

4. RESULTS ANALYSIS

The results demonstrate the effectiveness of the proposed AI-driven biscuit defect detection system in accurately classifying different types of defects. Multiple machine learning models, including ETC, LDA, and LGBM, were evaluated and compared with the proposed ResNet-based CNN model. Among them, the ResNet CNN achieved the highest performance with an accuracy of approximately 98.98%, significantly outperforming the traditional models. Evaluation metrics such as precision, recall, F1-score, confusion matrices, and ROC-AUC curves confirmed the superior classification capability of the deep learning approach. The system was also able to reliably distinguish between defect categories such as color, shape, object defects, and defect-free samples. The results validate that the proposed model provides a highly accurate, efficient, and scalable solution for automated biscuit quality inspection in food manufacturing.

The figure 3 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 100 Color Defect, 379 No Defect, 122 Object Defect, and 369 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.

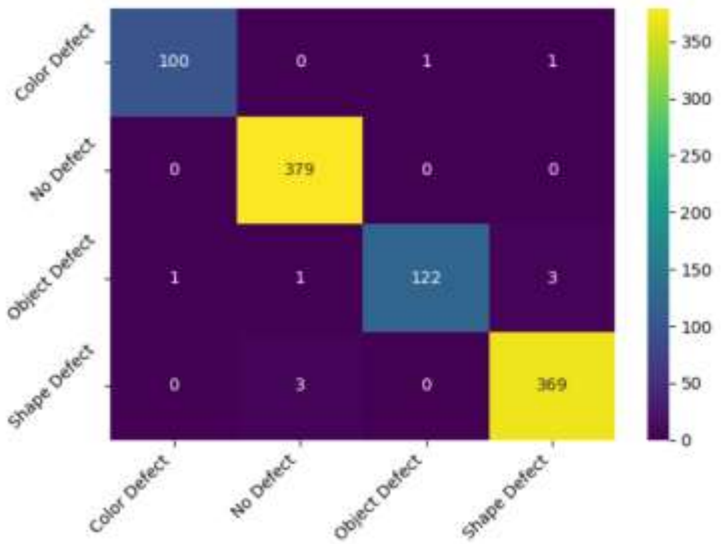

Figure 3: Illustration of confusion matrix using proposed CNN Model

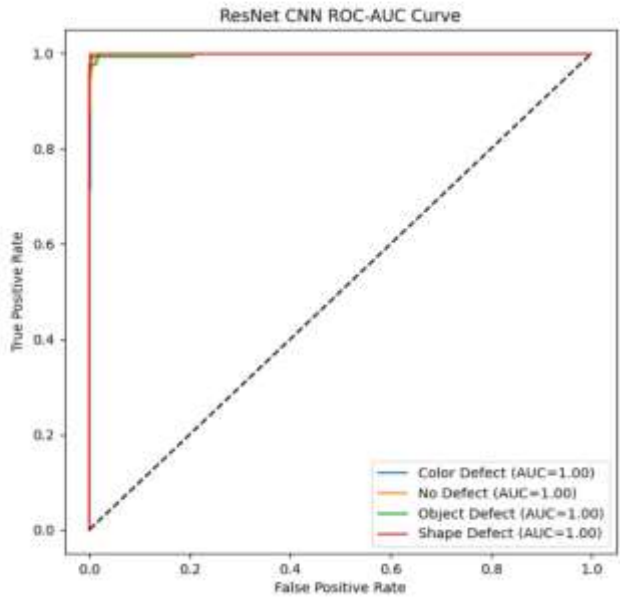

Figure 4: ROC-AUC curve Obtained using proposed ResNet-based CNN Model

The figure 4 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.

Figure 5: Real time prediction obtained using telegram bot

Figure 5 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.

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

Model	Accuracy	Precision	Recall	F1-Score
ETC	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 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.

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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