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Artificial Neural Network for Corn Quality Classification Based on Seed Damage and Aflatoxin Attributes

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ABSTRACT

Corn plays a critical role in Indonesia's agricultural sector, functioning as both a staple food for human consumption and a key component of livestock feed. However, its quality is frequently compromised by factors such as mechanical damage during harvesting, fungal contamination, and fluctuating climate conditions, all of which pose challenges to maintaining consistent standards. Traditionally, corn quality classification relies on manual methods, which are not only time-consuming but also prone to human error and inconsistency. To address these limitations, this study employs a Neural Network approach to classify corn into two distinct categories: breeder and commercial grades. The research utilizes a dataset of 2,026 records, meticulously divided into 70% for training, 20% for validation, and 10% for testing, ensuring robust model evaluation. The methodology includes comprehensive data preprocessing, feature standardization to normalize input variables, and hyperparameter optimization, with the model trained over 100 epochs using a batch size of 32 and a learning rate of 0.001. The results demonstrate exceptional performance, achieving an accuracy of 99.5%, precision of 98.3%, recall of 100%, and an F1-score of 99.1%, as validated by a confusion matrix that highlights the model's classification reliability. This automated system significantly enhances the efficiency and accuracy of corn quality assessment, offering a scalable solution to replace outdated manual techniques. By providing a reliable tool for quality differentiation, this study supports Indonesia's agricultural and livestock industries, with potential for broader application in optimizing crop management and ensuring food security under varying environmental conditions.

1. Introduction

Corn is one of Indonesia's strategic food commodities, playing a crucial role in national food security and the economy security and the economy. As the primary carbohydrate source after rice, corn is consumed in various forms, such as corn rice and other processed products [1]. In addition to being a staple food, corn serves as a key component in the livestock feed industry, particularly for poultry, with more than 55% of the national corn production allocated for this purpose [2]. The high demand for corn in the livestock sector highlights the importance of stable and high-quality production to support food security and related industries [3][4]. Nevertheless, corn production in Indonesia faces several challenges that may affect yield and product quality. Pest infestations, such as Java Downy

Mildew, and limitations in transportation infrastructure to export ports are among the primary obstacles in the national corn supply chain [2],[5]. Fluctuations in production also lead to market instability, impacting corn prices and its derivative products, including animal feed and other food ingredients [6]. Therefore, innovative efforts are needed to enhance corn productivity and quality to meet bot domestic and export market demands.

Factors contributing to the decline in corn quality can be categorized into three main groups: mechanical damage, environmental and biological factors, and climatic conditions. Mechanical damage occurring during harvesting, drying, and processing can cause kernel breakage and cracking, increasing the risk of spoilage and reducing market value [7][8]. Additionally, fungal infections, such as those caused by Fusarium and Aspergillus, can lead to mycotoxin contamination, which poses health risks to both humans and livestock [9]. Meanwhile, climatic conditions such as drought and cold stress also contribute to reduced quality and yield [10]. Manual quality assessment of corn is still widely used in Indonesia; however, this method has significant limitations. Visual inspection requires extensive labor, is time-consuming, and often results in inconsistencies due to human subjectivity [11][12]. Moreover, manual methods are inefficient for industrial-scale operations, which require rapid and accurate quality assessments. Therefore, automated methods are needed to improve efficiency and accuracy in corn quality classification. The classification of corn quality is a crucial aspect of the agricultural supply chain, particularly in distinguishing between seed corn and commercial corn. Accurate classification enables the alignment of corn with specific market demands, such as direct consumption, animal feed, or industrial raw materials [13][14]. Several morphological characteristics are essential for assessing corn quality, including kernel length, width, and shape [15], [16], as well as color features extracted from images [16] and the texture and internal structure of the kernel [17]. In addition to enhancing market value, precise classification can reduce the risk of product rejection due to substandard quality [18]. Furthermore, food safety can be better ensured by maintaining low levels of mycotoxins in consumed corn [19].

Machine learning-based methods have been widely applied in corn quality classification, yielding promising results. Several commonly used algorithms include Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Decision Tree (DT), which have demonstrated high accuracy in detecting corn quality and variety [20]-[25]. Additionally, Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) have proven to be effective in classifying the quality and damage of corn kernels or seeds, achieving higher accuracy compared to conventional methods [15],[17],[26][27]. Another study utilized a ResNet50-based Convolutional Neural Network (CNN) for Milkfish classification [28].

The Artificial Neural Network (ANN) approach in corn quality classification demonstrates significant potential in enhancing efficiency and accuracy in the agricultural sector. Various ANN methods have been successfully applied to classify corn kernels based on morphological characteristics, color, and texture. One such approach is the Multilayer Perceptron Neural Network (MLPNN), which has achieved an accuracy of 91.85% in distinguishing between damaged and intact corn kernels [26]. The MLPNN classifier can be adapted to differentiate between seed corn and commercial corn by training it on relevant morphological and color features. Additionally, the Self-Adaptive Back Propagation Neural Network (BPNN), combined with hierarchical clustering, has demonstrated an accuracy of over 90% in classifying corn kernels into multiple categories [15]. This approach can be tailored to classify seed corn and commercial corn by selecting appropriate features and training the network accordingly. On the other hand, Convolutional Neural Networks (CNNs) have also been widely used in image-based corn quality classification. For instance, Deep Convolutional Neural Networks (DCNNs) have achieved an accuracy of 97.6% in classifying corn seed varieties and quality [17], making them suitable for distinguishing seed corn from commercial corn by training the network on corn kernel images. Moreover, custom CNN models, incorporating residual networks and specialized layers, have demonstrated high accuracy, reaching up to 99.3% in classifying corn seed quality [27]. These models can be further adapted to classify seed corn and commercial corn by focusing on specific quality attributes. By implementing the appropriate ANN methods, this study aims to achieve high accuracy levels that can serve as a reference for the industry in establishing corn quality standards, thereby streamlining production processes and improving efficiency in the agricultural sector.

2. Methods

To address the challenges encountered during the research process, a structured research methodology was implemented to identify appropriate solutions. This study employs data processing techniques using data mining, specifically utilizing the Neural Network algorithm.

2.1. Data Collection

The dataset utilized in this study comprises an internal dataset representing the quality of corn harvests, obtained from a case study conducted at PT BISI International Tbk. Initially recorded in Microsoft Excel format, the data was later converted into CSV (Comma-Separated Values) format for analysis. The attributes included in the corn harvest quality dataset are presented in Table 1. The dataset consists of 2,026 records, with the quality attribute serving as the target variable. This variable is classified into two categories: breeder and commercial. The breeder category represents the highest quality level (grade one), while the commercial category corresponds to the second level of corn quality. In this dataset, Class 0 represents the commercial grade, whereas Class 1 denotes the breeder grade.

Table 1. Data Attributes

Attribute	Data Type	Description
Damage Seed	Floating	Total percentage of damaged seeds
Broken Seed	Floating	Total percentage of broken seeds
Moldy Seed	Floating	Total percentage of moldy seeds
Foreign Material	Floating	Total percentage of foreign material mixed with corn seeds
Aflatoxin	Floating	Percentage of corn seeds contaminated with chemicals
Quality		Quality Integer Quality parameter of corn seeds

2.2. Data Preprocessing

Data preprocessing in this study involves preparing the dataset, including handling missing values. The primary objective of this step is to ensure that the data used for analysis, reporting, and decision-making is accurate, consistent, and reliable. In the case of the corn harvest quality dataset, among the 2,026 records, one record was identified with missing data in the foreign material attribute. A common approach to addressing incomplete data is to impute the missing values, thereby maintaining data integrity and enhancing the quality of analysis.

To resolve this issue, the mean imputation method was applied. This technique involves calculating the mean of all available values in the foreign material column and substituting the missing data with this mean value. Mean imputation helps preserve the original data distribution without significantly altering the descriptive statistics of the dataset. The formula for mean imputation is presented in Equation (1), where n represents the total number of complete records.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \text{ [29]} \quad (1)$$

2.3. Data Splitting

In this experiment, the dataset consisting of 2,026 records is divided into training data, validation data, and testing data with specific percentage allocations. Training data comprises 70% of the dataset, validation data 20%, and testing data 10%. Validation data serves as a subset used to monitor the model's performance during training. Unlike training data, it is not directly used for model training but rather helps prevent overfitting and assists in hyperparameter selection. In contrast, testing data is utilized solely for the evaluation process and is not involved in training the Neural Network model.

2.4. Feature Standardization

Feature standardization in the dataset involves transforming the data by scaling each feature to have a mean of 0 and a standard deviation of 1, achieved by subtracting the mean value $\bar{x}$ from each feature's value x_i and dividing the result by the standard deviation Z_i, as expressed in Equation (2), resulting in a standardized value Z_i for the i-th data point, with the primary goal of ensuring all features

are on a uniform scale to prevent any single feature from disproportionately influencing the model due to a larger value range.

$$Z_i = \frac{x_i - \bar{x}}{S} \text{ [29]} \quad (2)$$

2.5. Neural Network Model

The architecture of the Neural Network model used in this study is designed for binary classification and consists of two hidden layers and one output layer. The ReLU activation function is applied in the hidden layers to enhance learning representations, while the sigmoid activation function in the output layer facilitates the determination of the output class.

2.5.1. Hyperparameter

A Neural Network is structured as a sequential model consisting of an input layer, hidden layers, and an output layer. Each neuron in the Neural Network processes information by computing a weighted sum of its inputs, followed by the addition of a bias term. This computation is mathematically represented in Equation (3).

A Neural Network, structured as a sequential model with an input layer, hidden layers, and an output layer, processes information by computing a weighted sum of inputs plus a bias term in each neuron, as shown in the equation (3), where W is the weight, x is the input, and b is the bias, followed by activation functions like ReLU (equation (4)), in hidden layers and sigmoid (equation (5)), in the output layer for binary classification (0 or 1), based on five input features in this study. The hidden layers, optimized through hyperparameter tuning of layer and unit counts, use ReLU and dropout (rate 0-1) to prevent overfitting, while the model minimizes error using binary cross-entropy loss (equation (6)), and the Adam optimizer (equation (7)), adjusting weights over multiple epochs and mini-batch gradient descent for efficient training.

$$y = Wx + b \text{ [30]} \quad (3)$$

$$ReLU(x) = \max(0, x) \text{ [30]} \quad (4)$$

$$Sigmoid(x) = \frac{1}{1 + e^{-x}} \text{ [30]} \quad (5)$$

$$L(y, p) = -(y \log(p) + (1 - y) \log(1 - p)) \text{[30]} \quad (6)$$

$$W_t = W_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \text{ [30]} \quad (7)$$

2.6. Data Training

In this stage, the learning process is executed on the dataset to produce a trained model, which is subsequently stored for the testing phase, utilizing the training dataset to fine-tune the weights and biases of each neuron layer. The training process incorporates several key parameters: the training dataset, comprising standardized features and corresponding target labels, is employed to teach the model to recognize patterns for accurate predictions; the model undergoes 100 epochs, meaning the full dataset is processed 100 times to deepen learning and minimize errors; and the data is split into batches of 32 samples, with each batch incrementally updating the model's weights via backpropagation, a smaller batch size enhancing learning speed and reducing memory demands. Additionally, a validation dataset, consisting of standardized features and target labels, is used to monitor the model's performance on unseen data, evaluating its generalization ability at the end of each epoch.

2.7. Model Evaluation

In this data testing, a confusion matrix is used, as shown in Fig. 1, to analyze the model's prediction results and determine the accuracy obtained from the system's operation. A confusion matrix is a table

used to evaluate the performance of a classification model, particularly in binary or multi-class classification. The elements within the confusion matrix are as follows:

- Class 0 and Class 1: These represent the labels for the two classes modeled by the classification system. Here, Class 0 corresponds to commercial, and Class 1 corresponds to breeder.
- True Label: The rows in the confusion matrix indicate the actual labels from the test data.
- Predicted Label: The columns represent the labels predicted by the model for the given data.

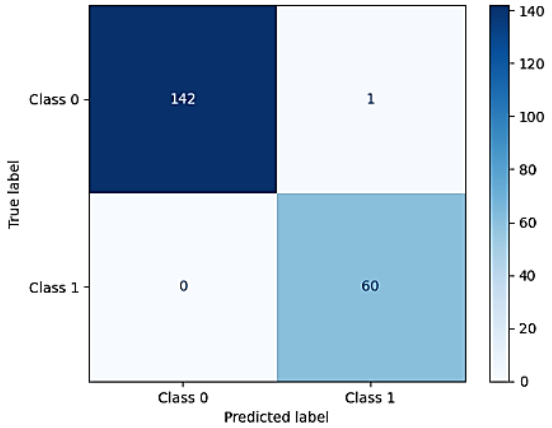


Fig. 1. Confusion Matrix

2.8. Output

The output obtained is the accuracy percentage of the Neural Network model that has been developed. This result serves as the basis for drawing conclusions from the conducted testing. Additionally, other evaluation metrics such as accuracy, loss, precision, recall, and F1-score are also considered. These metrics are used to further assess whether the model performs efficiently and effectively.

3. Results and Discussion

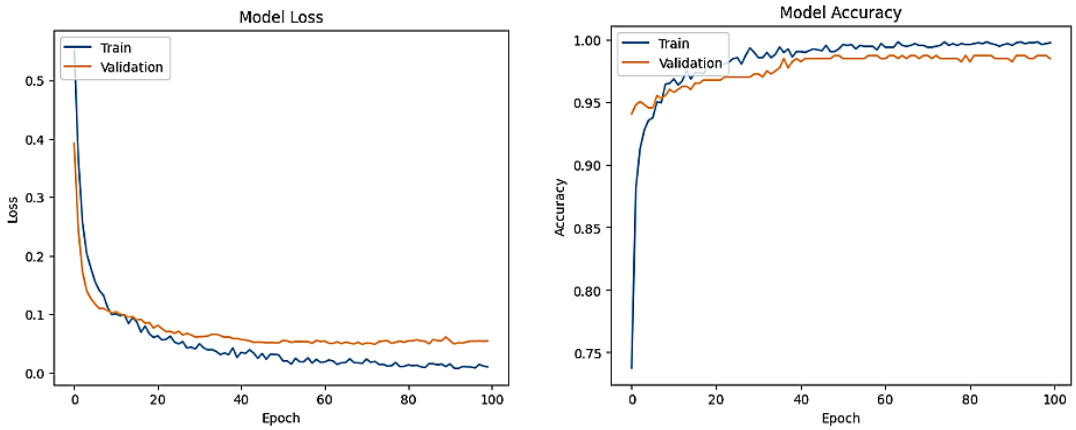
This section provides an explanation and discussion of the results obtained from the training and testing phases of applying the Neural Network classification algorithm for determining corn quality.

3.1. Training Data Testing Results

The training data testing was conducted using 1,417 samples (70%) of the total dataset, while 406 samples (20%) were used as validation data. The model was trained with a learning rate of 0.001, 100 epochs, and a batch size of 32. In Fig. 2, the best epoch for training and validation loss occurred at epoch 70, whereas in Figure 2 the best epoch for training and validation accuracy was observed at epoch 49. The training accuracy was exceptionally high, almost reaching 100%, while the validation accuracy remained stable at around 98%. This indicates that the model successfully learned patterns in the training data and was able to maintain good performance on the validation data.

At epoch 1, the training accuracy started at 63.60% with a loss of 0.6302, while the validation accuracy was 94.09% with a loss of 0.3917. Despite the relatively low training accuracy at this stage, the validation accuracy was already high. This suggests that either the dataset was not overly complex or the model quickly learned the primary patterns. By epoch 10, the training accuracy increased to 96.61%, while the validation accuracy reached 96.06%. The decreasing loss indicates that the model continued to improve in minimizing errors. At epoch 20, the training accuracy reached 98.63%, and the validation accuracy was 96.80%. After epoch 20, accuracy improvements became slower and started stabilizing. The training accuracy reached 99.83% at epoch 100, while the validation accuracy remained steady at around 98% after epoch 40. The validation loss began to stagnate and slightly increase after epoch 50. The training loss decreased significantly at the beginning and continued to approach zero by the end of training, indicating that the model effectively minimized errors in the training data. However, the validation loss remained higher than the training loss, but the difference was within a reasonable range, suggesting that no severe overfitting was present.

From the figures above, it can be observed that the first epoch took two seconds with 6ms per step, which was longer compared to subsequent epochs due to the data loading process into memory. From epoch 2 to epoch 100, the average time per epoch was 0 seconds, with 2ms to 6ms per step. After initialization, the training time per epoch became significantly faster and more consistent. The total time required for training and validation across 100 epochs was approximately 17 seconds. The short per-epoch training time demonstrates efficiency in the training process, which can be attributed to the relatively small model size and the use of adequate hardware resources.



(a) (b)

Fig. 2. (a) Training and Validation Loss, and (b) Training and Validation Accuracy

3.2. Testing Data Evaluation

The testing phase was conducted using 203 samples (10%) of the total dataset. The total time required for testing was 0 seconds, with an average of 3ms per step. Explanation of Fig. 3 is precision for class 0 is 1.00, meaning that 100% of predictions classified as class 0 were correct. Precision for class 1 is 0.98, meaning that 98% of all predictions classified as class 1 were correct, while the remaining 2% were incorrect. Recall for class 0 is 0.99, indicating that the model correctly identified 99% of all actual class 0 samples. Recall for class 1 is 1.00, meaning that the model correctly identified 100% of all actual class 1 samples. F1-score for class 0 is 1.00, and for class 1, it is 0.99, demonstrating that the model has an excellent balance between precision and recall. Support, representing the number of actual samples in each class, consists of 60 samples from class 1 and 143 samples from class 0 in this dataset. The accuracy shown in the classification performance report is 1.00, meaning that the model correctly predicted all test data without any errors.

	precision	recall	f1-score	support
Class 0	1.00	0.99	1.00	143
Class 1	0.98	1.00	0.99	60
accuracy			1.00	203
macro avg	0.99	1.00	0.99	203
weighted avg	1.00	1.00	1.00	203

Fig. 3. Classification Model Performance Report

From the explanation above, it is evident that high accuracy is directly correlated with high precision and recall values. Precision focuses on positive predictions. It measures how many of the model's positive predictions were actually correct (true positives - TP). A higher precision indicates that the model makes fewer false positive errors (FP), leading to improved accuracy. Recall measures the model's ability to detect all actual positive samples (TP). Recall is crucial in scenarios where missing positive predictions (false negatives - FN) should be avoided. F1-score balances the trade-off between precision and recall. It is more relevant than accuracy alone, especially when the goal is to minimize false positives (FP) while capturing all true positives (TP) and reducing false negatives (FN).

In this case study, where the objective is to classify corn quality, precision is more critical to maintain quality consistency in the eyes of consumers. Since breeder-quality corn (Grade 1) is sold at

a higher price, misclassifying commercial-quality corn (Grade 2) as breeder-quality could lead to consumer distrust, negative claims, and financial losses.

3.3. Discussion

In this study, "Application of Classification Algorithms in Determining Corn Quality," the model achieved an accuracy of 99.51% using the following hyperparameters: learning rate of 0.001, 100 epochs, and a batch size of 32. Based on the training and testing process results, the model can be considered accurate, as it achieved a high accuracy score on the test data. A high accuracy on test data indicates that the model successfully generalizes patterns from the training data to new data without merely memorizing the training set.

From the training log, the first epoch took 2 seconds per batch with 6ms per step, which was longer compared to subsequent epochs. After the first epoch, the training speed stabilized at 3ms per step, with a total time per epoch of approximately 0-1 second, resulting in a total training time of 15.365 seconds. The testing phase was completed in 2ms, indicating that the evaluation process was highly efficient and fast. The total time required to test the dataset was only 0.014 seconds (14 milliseconds), meaning the model can make predictions at high speed. Thus, the total time required for training and testing the model was approximately 15.38 seconds.

When comparing corn kernel classification studies using other methods, such as Jihad Ardiansyah's research, which classified corn kernels using the discrete wavelet transform and support vector machine (SVM) method, an accuracy of 93.33% was achieved with a computation time of 0.6384 second [23]. This indicates that the Neural Network model in this study outperforms both in accuracy and computation time. Similarly, Ula Delfana Rosiani's research classified corn kernel quality using the K-Nearest Neighbor (K-NN) method, achieving an accuracy of 76.67% [24]. Additionally, Moch. Lutfi's study, titled Implementation of K-Nearest Neighbor and Bagging Methods for Production Quality Classification, obtained the highest accuracy of 79.30% [25]. Despite these results, the Neural Network method still demonstrates superior performance. Furthermore, in Alfa Saleh's study on the utilization of data mining techniques for determining corn quality standards, three methods were compared: Naïve Bayes, Decision Tree, and Support Vector Machine (SVM). The results showed that Support Vector Machine (SVM) achieved a success rate of 94.03%, Decision Tree (C4.5) had an average classification accuracy of 86.17%, Naïve Bayes had an average classification success rate of 82.33% [31]. While SVM produced high accuracy, when compared to the Neural Network model developed in this study, the Neural Network method remains superior in overall performance.

It can be observed that the Neural Network model outperforms other methods. This is evident in Yunarto's study, which compared the Backpropagation algorithm and Support Vector Machine (SVM) for corn kernel classification. The results showed that the Backpropagation (Neural Network) algorithm achieved better recognition accuracy, with an average accuracy of 97.5%, compared to the SVM algorithm, which only achieved an average accuracy of 97.1%. Additionally, Backpropagation was significantly faster, with the shortest computation time of 0.8825 seconds, compared to the SVM algorithm, which had the shortest computation time of 1.6845 seconds [32]. Thus, the Neural Network model developed in this study outperforms other classification methods used in previous research. This is mainly due to the hyperparameter tuning applied to the Neural Network model, which significantly impacts both accuracy and computational speed. Several factors contribute to the model's efficiency; the number of neurons (64, 32) is not excessively large, making the computation lighter and more efficient. The model consists of only two hidden layers, which makes it faster compared to models with a higher number of layers while still being deep enough to learn complex patterns. The use of the ReLU activation function speeds up operations and helps prevent the vanishing gradient problem. The implementation of dropout (0.5) effectively prevents overfitting during training.

The confusion matrix provides insights into the number of correct and incorrect predictions for each class. Based on True Positives (TP) and True Negatives (TN), the model effectively classifies both positive (Class 1) and negative (Class 0) samples. The number of false positives is minimal (only one), and there are no false negatives. This result suggests that the model rarely makes incorrect predictions and effectively distinguishes between the two classes. If the model were to produce a high number of errors in one of the classes, it would be necessary to reconsider adjustments to the model.

The additional evaluation metrics, precision, recall, and F1-score, indicate strong performance, particularly for the positive class. Precision for the positive class is 0.983, meaning that 98.3% of all positive predictions were correct. Recall for the positive class is 1.00, meaning that the model successfully detected all positive cases without missing any. F1-score is close to 1, indicating that the model is not only accurate but also well-balanced in identifying both classes, with no significant bias toward either class.

Examining the loss graph, the early stages of training show a significant decrease in both training and validation loss. After approximately 20 epochs, the training loss graph stabilizes, demonstrating that the model continues to improve its performance on the training data. Although there is a slight difference between training and validation loss, there is no drastic increase in validation loss, indicating that the model remains stable and does not experience significant overfitting while maintaining good generalization capabilities.

Dropout played a crucial role in preventing overfitting, as observed in the conducted experiments. With a dropout rate of 0.5, the model maintained a balance between training and validation without clear signs of overfitting. Compared to lower dropout rates, dropout 0.5 introduced a higher level of regularization, significantly reducing overfitting and improving the model's ability to generalize to validation data. Overall, based on accuracy, precision, recall, F1-score, confusion matrix, and loss analysis, the model demonstrates high performance and accuracy in classifying data correctly. The choice of dropout 0.5 proves to be an effective method in reducing overfitting, providing a well-balanced trade-off between regularization and performance, with a minimal gap between training and validation accuracy.

4. Conclusion

This study explored the application of Neural Network algorithms for classifying corn quality, which is a crucial aspect of the agricultural supply chain, particularly in distinguishing between breeder (Grade 1 quality) and commercial (Grade 2 quality) corn for livestock feed. The classification was conducted using a dataset of 2,026 data points, divided into 70% training data (1,417 data points), 20% validation data (406 data points), and 10% test data (203 data points). To optimize model performance, hyperparameter tuning was applied with one input layer, two hidden layers, two dropout regularization layers, one output layer, 100 epochs, a batch size of 32, and a learning rate of 0.001. The evaluation metrics demonstrated the effectiveness of the Neural Network model, achieving an accuracy of 99.5%, recall of 100%, precision of 98.3%, and an F1-score of 99.1%. These results indicate that the Neural Network model provides a highly accurate classification of corn quality, supporting efficiency improvements in the agricultural sector by automating the quality assessment process. The high performance of this model suggests its potential application in industrial-scale operations, contributing to better quality control and decision-making in the corn supply chain. Future work may explore the integration of the model with IoT-based monitoring systems, validation using external datasets, and comparison with interpretable machine learning models for industry transparency.

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