Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 11, 1389-1401
2025
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v9i11.11220

Palm fruit ripeness classification using BorneoNet for improved accuracy in precision agriculture

Nurahman[1*], Minarni[2], Abdul Aziz[3], Lili Winarti[4], Eddy Mashami[5], Dwi Wahyu Prabowo[6]
[1,2,3,6]Department of Information System, Faculty of Agriculture, Universitas Darwan Ali, Sampit, Indonesia; nurahman@unda.ac.id (N.).
[4]Department of Agribusiness, Faculty of Agriculture, Universitas Darwan Ali, Sampit, Indonesia; liliwinarti14@gmail.com (L.W.).
[5]People's Representative Council of East Kotawaringin Regency, Indonesia; eddymashamy@gmail.com (E.M.).
[6]Department of Information System, Faculty of Computer Science, Universitas Darwan Ali, Sampit, Indonesia.

Abstract: This study aims to classify palm fruit ripeness using the proposed Borneo Neural Network (BorneoNet) to improve accuracy over traditional models and provide a practical solution for precision agriculture. A novel dataset of RGB images was collected and categorized into three ripeness stages: ripe, half ripe, and unripe, then divided into 50 percent training, 25 percent validation, and 25 percent testing subsets. The BorneoNet architecture consists of three convolutional layers with batch normalization and max-pooling, followed by two fully connected layers. Its performance was compared with kNN, Naive Bayes, SVM, Random Forest, and XGBoost using accuracy, precision, recall, F1-score, and Kappa metrics, while the McNemar test was used to confirm statistical significance. The findings showed that BorneoNet outperformed all traditional models with an accuracy of 0.8125, a precision of 0.8182, a recall of 0.7899, an F1-score of 0.7848, and a Kappa value of 0.7134, indicating strong agreement with the true labels. Overall, the results suggest that BorneoNet is a reliable and efficient model with lower computational complexity than traditional and deep CNN architectures. The practical implications include its potential use as a lightweight real-time tool for farmers, with future development focusing on dataset expansion and integration into mobile applications to support precision agriculture.
Keywords: *BorneoNet, Image classification, Palm fruit ripeness, Precision agriculture.*

1. Introduction

Palm oil is a leading agricultural product with significant contributions to both the national economy and rural livelihoods [1-3]. As the number of palm oil farmers increases, determining the optimal maturity of palm fruits becomes crucial for ensuring high-quality yields. Harvesting before the optimal ripeness stage can significantly affect both the quality of the current yield and fruit production in subsequent harvests [4-6]. Therefore, farmers must be adept at identifying the appropriate maturity of palm fruits before harvesting. Ensuring optimal harvest timing requires an in-depth understanding of palm fruit development and strict adherence to established harvesting guidelines [7-10]. This knowledge is fundamental for maintaining the quality and productivity of palm oil plantations in the long term.

In our previous study, Ragil and Nurahman [11], we developed a classification model for palm fruit ripeness using the k-Nearest Neighbors (K-NN) method based on RGB and gray level co-occurrence matrix (GLCM) features. Although the K-NN model achieved its highest accuracy of 68% at k=1, the structured approach used in the training limited the effectiveness of the ripeness classification. The challenges faced in implementing this approach highlight the need for more advanced methods that can

History: Received: 24 September 2025; Revised: 6 November 2025; Accepted: 10 November 2025; Published: 28 November 2025
* Correspondence: nurahman@unda.ac.id

handle the complexity of data more effectively. Furthermore, the technical skills required to operate and maintain such systems present barriers for practical agricultural implementation.

To address these challenges, a well-designed model capable of improving accuracy and reducing complexity is necessary. This requires collaboration between IT experts, agricultural specialists, and stakeholders to create an effective and sustainable solution for farmers and support the local precision agriculture community.

Deep learning has emerged as a promising solution for tackling such challenges in precision agriculture [12]. One of the most popular approaches in deep learning for image data is the Convolutional Neural Network (CNN) architecture, which is specifically designed to handle image data [13]. CNNs consist of multiple layers where convolution operations are performed to detect important features in the input images. They are followed by nonlinear activation functions like ReLU and pooling layers that reduce the image dimensions. The model typically consists of fully connected layers that produce classification outputs [14]. CNNs have demonstrated their ability to extract complex features effectively, making them suitable for various image processing tasks, including object recognition and classification [15-17].

Previous studies have shown the effectiveness of CNN models in a variety of contexts. For instance, CNN models have been utilized to classify various agricultural products, thereby enhancing the efficiency and accuracy of crop management practices [18, 19]. A study by Reshi et al. [20] demonstrated that a CNN model could achieve up to 99.5% accuracy when classifying processed X-ray images, proving the power of CNNs in extracting crucial information from visual data. Furthermore, the ability of CNNs to recognize spatial patterns and extract diverse properties from images has been highlighted in the literature, reinforcing their utility in precision agriculture applications [21]. Recent studies have also explored non-visual and chemical-based approaches for ripeness assessment. A notable work by Tzuan et al. [22] utilized Raman spectroscopy to identify molecular characteristics such as protein, lipid, carotene, and guanine/cytosine, and employed an ANN model, achieving 97.9 percent accuracy in classifying oil palm fruit ripeness. Although highly accurate, this spectroscopy-based method requires specialized instruments and is less practical for field deployment compared to image-based techniques.

Recent developments in image-based artificial neural networks for precision agriculture also reinforce the importance of automated fruit assessment. A recent systematic literature review [23] highlighted that CNN-based architectures, including VGG16 and ResNet50, consistently achieve high accuracy across crops such as mango, apple, lemon, and coffee, with reported performance reaching 83 to 99 percent. The review further emphasizes the growing role of lightweight models and the integration of hardware–software pipelines for real-time ripeness detection and harvest decision support, while also noting the underutilization of vegetation indices and infrared imaging in fruit-specific quality evaluation. These insights confirm the relevance of developing efficient image-based models for practical harvest monitoring and support the need for lightweight architectures suitable for field deployment.

Lightweight convolutional neural networks have also gained significant traction in recent agricultural applications. Guo et al. [24] introduced LWheatNet, a lightweight CNN integrating mixed channel–spatial attention and stacked inverted residual convolution blocks, achieving 98.59 percent accuracy while maintaining a compact 1.33-million-parameter size. The model outperformed classical networks such as AlexNet, VGG16, MobileNetV2, MobileNetV3, and ShuffleNetV2, demonstrating that efficient architectures can deliver high performance even under limited computational resources. These findings reinforce the growing need for resource-efficient CNN models that can operate in real-time on low-power agricultural devices, further supporting the relevance of lightweight solutions for practical field deployment.

Drawing from the limitations identified in our previous study and the potential of deep learning methods, this research proposes a new approach to classify palm fruit ripeness using a novel dataset and a Borneo Neural Network (BorneoNet). BorneoNet is a shallow CNN that differs from deep CNN

architectures to bring the best trade-off between low model complexity and computational efficiency, making it especially ideal for real-world agricultural settings where computational resources may be limited. Utilizing BorneoNet, we aim to enhance the model's ability to classify ripeness levels accurately while reducing computational effort to enable practical accessibility for use by farmers.
The main contributions of this study are as follows:

1. Proposal of a new palm fruit ripeness dataset: The collection and development of a new dataset specifically tailored for the classification of palm fruit ripeness is a critical component of this study. The dataset aims to capture the unique characteristics of palm fruit at different stages of ripeness to enhance classification accuracy.
2. Application of BorneoNet for palm fruit ripeness classification: The introduction of BorneoNet provides a novel and efficient approach to ripeness classification, specifically designed to match the characteristics of the palm fruit dataset while maintaining computational efficiency.

At present, deep learning models, especially convolutional neural networks (CNNs), are quite effective and operate with high precision in machine-processing tasks, which elicits the motivation of both industry and academic fields [25, 26]. The goal of the study is to take advantage of these approaches to reach a palm fruit ripeness classification accuracy higher than the 68% achieved in our previous work [11]. Here, the architecture of BorneoNet not only achieves higher accuracy but also facilitates a lightweight, straightforward, and relevant solution that could potentially be easily deployable by local farmers.

In conclusion, this study presents an innovative approach for classifying palm fruit ripeness using a novel dataset and BorneoNet. By optimizing the model architecture and employing data augmentation, we aim to achieve significant improvements in classification accuracy, which will ultimately benefit the palm oil industry by providing farmers with an effective tool for precision agriculture. The successful implementation of this technology in East Kotawaringin will serve as a model for similar agricultural applications, potentially transforming how farmers determine optimal harvest times and contributing to sustainable agricultural practices.

2. Materials and Methods

Figure 1 illustrates the research workflow designed to address the challenges of classifying oil palm fruit ripeness levels. The process begins with the Palm Oil Fruit Data Acquisition stage, which focuses on collecting fruit images under various environmental conditions. Each image is categorized into three primary classes: unripe, half-ripe, and ripe palm fruit. This categorization forms a crucial foundation for developing an accurate classification system, as each class exhibits distinct visual characteristics in terms of color, texture, and shape.

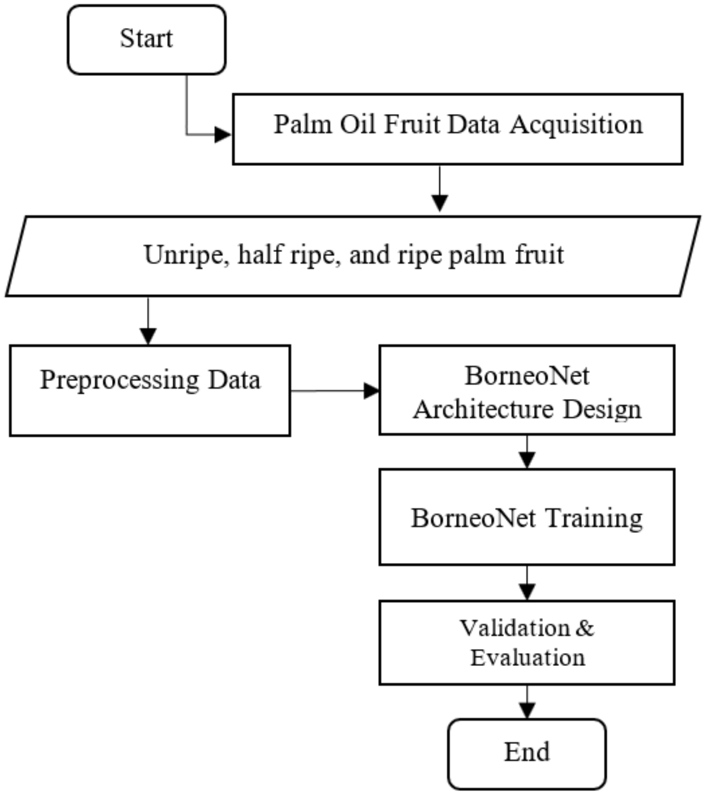

Figure 1.
Palm fruit ripeness classification pipeline.

Following the data acquisition phase, the next stage involves Data Preprocessing, which includes image size normalization, quality enhancement, and data augmentation to expand dataset diversity. These steps are essential to reduce noise and ensure optimal performance of the deep learning model. Subsequently, the BorneoNet architecture design is developed as a convolutional model specifically designed to detect and differentiate ripeness levels of palm fruits based on visual patterns. The architecture structure is tailored to the dataset's complexity and the intended classification objectives.

The subsequent stage involves BorneoNet Training, where the model is trained using preprocessed data to learn the essential features of each fruit category. Once training is completed, the validation and evaluation process is conducted to assess the model's performance using metrics such as accuracy, precision, and F1-score. The evaluation outcomes serve as a basis for determining the system's effectiveness and its potential real-world application. Overall, the process depicted in the diagram ensures that every aspect of the study is conducted systematically, resulting in a reliable and well-validated predictive model.

2.1. Dataset

The dataset in our research consisted of images classified into three categories: ripe palm fruit, half-ripe palm fruit, and unripe palm fruit. Each category contains a representative set of images that capture variations in the color, texture, and shape of the oil palm. The dataset consisted of 254 samples (91 ripe, 72 half-ripe, and 91 unripe). The data collection involved capturing images from various angles and lighting conditions to ensure diversity within the dataset. These images were used to train a CNN model for classifying the ripeness of oil palm fruits. Each image in the dataset underwent preprocessing to improve quality and consistency. Using a well-structured dataset, we aimed to achieve a higher level

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 11: 1389-1401, 2025
DOI: 10.55214/2576-8484.v9i11.11220

of accuracy, surpassing previous research on classification tasks. Our dataset can be downloaded from this link: https://data.mendeley.com/datasets/zrcf6v69y8/1.

(a) (b) (c)

Figure 2.
The sample dataset of palm fruits was categorized as (a) ripe, (b) half ripe, and (c) unripe.

Figure 2(a) presents a ripe oil palm fruit characterized by bright red and orange colors, indicating that the fruit is ready for harvest and is optimal for oil extraction. Figure 2(b) depicts a semi-ripe oil palm fruit with darker shades, ranging from reddish-brown to deep purple, suggesting that the fruit is partially mature but not yet ideal for harvest. Figure 2(c) shows an unripe oil palm fruit that remains predominantly dark in color, indicating that the fruit is still in its early developmental stages and is not ready for harvest. The level of ripeness is crucial for determining the optimal harvest time to maximize the oil yield.

2.2. k-NN

The K-Nearest Neighbors (KNN) algorithm employs the K closest data points from the training dataset to predict the value of a new sample. Euclidean distance is the most frequently employed metric for measuring proximity in KNN [27]. Euclidean distance was calculated using Equation (1).

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{p} (x_{ik} - x_{jk})^2} \qquad (1)$$

In this equation, x_i denotes the feature vector of the first data point, and x_j denotes the feature vector of the second data point. The terms x_{ik} and x_{jk} refer respectively to the values of the k -th feature for data points x_i and x_j. The variable p represents the total number of features considered in the calculation, and $d(x_i, x_j)$ expresses the Euclidean distance computed between the two data points.

2.3. Naive Bayes

Naive Bayes is a probabilistic machine learning algorithm based on Bayes' theorem [28]. The algorithm can determine the class of a sample based on the observed features and calculate the probability that the sample belongs to a particular label [29]. Classification using the Naive Bayes algorithm can be performed using Equation (2) [30].

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \qquad (2)$$

In Equation (2), $P(A|B)$ represents the posterior probability of class A given the evidence B. The term $P(B|A)$ denotes the likelihood, which expresses how probable the evidence B is when class A is true. The prior probability of class A is written as $P(A)$, while $P(B)$ is the marginal probability of observing the evidence B across all classes.

ISSN: 2576-8484
Vol. 9, No. 11: 1389-1401, 2025
DOI: 10.55214/2576-8484.v9i11.11220

2.4. Random Forest

The Random Forest (RF) method can be used to construct multiple decision trees and then combine their results to produce more accurate predictions. Each decision tree is built through an iterative data-splitting process, in which the data are divided into smaller subsets [31, 32]. This division is based on randomly selected features, which helps to increase the variability among trees. To determine how to split the data, the RF algorithm selects the splitting point that minimizes impurities within the resulting subsets. Impurity is typically measured using metrics such as entropy or the Gini index, which assess the homogeneity of subsets. Once the decision trees are built, the results from each tree are aggregated, and the final prediction is made through averaging or voting. This approach helps reduce the risk of overfitting because the variation between trees mitigates the impact of individual errors.

2.5. SVM

Support Vector Machine (SVM) operates by finding the optimal hyperplane that separates the data into two classes [33, 34]. For linear classification, SVM can be described using the following equation:

$$wx + b = 0. \qquad (3)$$

First, $\boldsymbol{w}$represents the weight vector that defines the direction and strength of the hyperplane in feature space. This vector plays a crucial role in determining the boundary between two classes. Where $\boldsymbol{x}$represents the feature vector that signifies the input data to be classified. Each data point has a distinct feature vector, depending on the dimensionality of the data. By maximizing the margin, the SVM solves the optimization problem as follows.:

$$min\frac{1}{2}\parallel w \parallel^2 \qquad (4)$$

subject to the following constraint:

$$y_i(wx_i + b) \geq 1. \qquad (5)$$

Next, $\boldsymbol{b}$ is the bias term that shifts the hyperplane away from the origin. This bias value helps to position the hyperplane more effectively within the feature space. In the equation $\boldsymbol{y_i(wx_i + b) \geq 1}$, $\boldsymbol{y_i}$ represents the class label for each data point, which can be either 1 or -1, indicating two different classes. This equation ensures that all points from the positive class are on one side of the hyperplane, whereas the negative class points are on the opposite side, maximizing the distance or margin between the hyperplane and the nearest data points from both classes. Finally, the SVM objective is to minimize the $\boldsymbol{min\frac{1}{2}\parallel w \parallel^2}$, which means the algorithm aims to maximize the margin while keeping the weight vector $\boldsymbol{w}$ small. This resulted in a more stable and robust model.

2.6. XGBoost

Extreme Gradient Boosting (XGBoost) is a widely used technique for building classification models in machine learning competitions and real-world applications [35]. This implementation of gradient boosting emphasizes speed and performance. XGBoost is based on the boosting technique of constructing simple models, such as decision trees, sequentially. Each subsequent model aims to correct the errors of the previous one. To prevent overfitting, regularization is incorporated into the loss function. The algorithm then proceeds to minimize this modified loss function. XGBoost integrates several elements into its theoretical framework. The basic formula for the loss function $\boldsymbol{L(y, \hat{y})}$ is presented in equation (6) below.

$$L(y, \hat{y}) = \sum_{i=1}^{n} l(y_i, \hat{y}_l) + \sum_{k=1}^{K} ⍰(f_k). \qquad (6)$$

The loss function $\boldsymbol{L(y, \hat{y})}$ measures how well the model predicts the outcome. In XGBoost, the loss function is typically quadratic for regression or logistic classification. The general formula for the loss function is given in the following equation.

$$\boldsymbol{L(y, \hat{y}) = \sum_{i=1}^{n} l(y_i, \hat{y}_l)}. \qquad (7)$$

ISSN: 2576-8484
Vol. 9, No. 11: 1389-1401, 2025
DOI: 10.55214/2576-8484.v9i11.11220

To prevent overfitting, XGBoost applies a regularization penalty represented by $\square(\boldsymbol{f_k})$.

$$\square(f_k) = \square K + \frac{1}{2}\square\|w\|^2. \qquad (8)$$

The model is then updated by adding a new tree to the previous model. The updated formula is as follows:

$$\hat{y}^{(t)} = \hat{y}^{(t-1)} + nf_t(x). \qquad (9)$$

Next, to build a tree, XGBoost selects the split at each node using a criterion that optimizes the reduction of the loss function. The reduction was calculated using the following equation:

$$\text{Gain} = \frac{1}{2}\left(\frac{(\sum g)^2}{\sum h+\lambda} - \text{bias}\right) \qquad (10)$$

Once all trees were generated, the prediction was derived by aggregating the results from every tree using the following formula:

$$\hat{y} = \sum_{t=1}^{T} f_t(x) \qquad (11)$$

XGBoost is an efficient and effective algorithm, particularly in machine learning competitions and real-world applications. Its advantages lie in its ability to handle large datasets and model complexity effectively, due to the use of regularization and gradient-based optimization.

2.7. BorneoNet

A CNN is an artificial neural network used for pattern recognition, classification, image processing, etc. [13]. In this study, we proposed a BorneoNet architecture for classifying the palm-ripeness dataset. Since the dataset size is relatively small and conventional CNN models require a large data training sample size, our proposed model is suitable for this study. The BorneoNet consists of a shallow-layer architecture that fulfils the needs of a small dataset. Table 1 summarizes the proposed BorneoNet architecture.

Table 1.
The proposed Borneonet architecture.

Layer Type	Unit/Nodes	Activation	Additional Layers
Input	-	-	-
Conv1	16 filters, 3 × 3	ReLU	BatchNorm
Max Pooling	2 × 2 pool_size	-	-
Conv2	32 filters, 3 × 3	ReLU	BatchNorm
Max Pooling	2×2 pool_size	-	-
Conv3	64 filters, 3 × 3	ReLU	BatchNorm
Max Pooling	2 × 2 pool_size	-	-
FC1	128	-	Dropout (50%)
FC2	3	-	-

The input size was 100 × 100 with three-channel RGB images of palm fruits. The BorneoNet model is a convolutional neural network designed for classifying palm fruit ripeness into three categories: ripe, half-ripe, and unripe. The architecture model includes three convolutional layers and then fully connected layers. We applied batch normalization and max pooling after each convolutional layer to decrease the dimensions spatially while preserving essential features for the classification task.

The input layer accepts RGB images with three channels that represent the red, green, and blue components of the image. The first convolutional layer (Conv1) applies 16 filters with a 3×3 kernel using ReLU as the activation function to introduce nonlinearity. Batch normalization follows this layer to improve training stability. A 2×2 max pooling with a stride of 2 reduces the spatial size by half.

Second convolutional layer (Conv2) uses 32 filters with a 3 × 3 kernel, followed by ReLU activation and batch normalization. A second 2 × 2 max pooling layer reduces the height and width. The third convolutional layer (Conv3) uses 64 filters, with the same kernel size and activation, before batch normalization and the final max pooling layer.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 11: 1389-1401, 2025
DOI: 10.55214/2576-8484.v9i11.11220

One more fully connected layer (FC1) is added after flattening the feature maps by the network, with 128 units and a ReLU activation function. To prevent overfitting, a dropout layer with a rate of 50% was applied. The last fully connected layer (FC2) presents class scores for three ripeness categories: ripe, half ripe, and unripe.

This architecture was designed to balance performance and computational efficiency. The use of shallow layers allows the model to extract relevant features while maintaining a low computational footprint. While batch normalization aids in stabilizing the learning process, dropout contributes to the model's ability to handle unseen data.

3. Results and Discussion

This research utilized the BorneoNet model to classify the ripeness of palm fruit using image processing. The dataset was split into three parts: a training set (50%), a validation set (25%), and a testing set (25%). The results for classifying the ripening of palm fruit with the use of an image-processing method are described here. A review and assessment of the results obtained in the processing and classification stages will be performed.

3.1. BorneoNet Training Performance

Figure 3 depicts the training and validation performance of the BorneoNet model. The training loss initially decreased rapidly and then plateaued at a lower value. Training accuracy steadily increased, exceeding 90%. While validation accuracy showed some fluctuations between 70-80%, indicating good generalization, it was not entirely consistent during the training process.

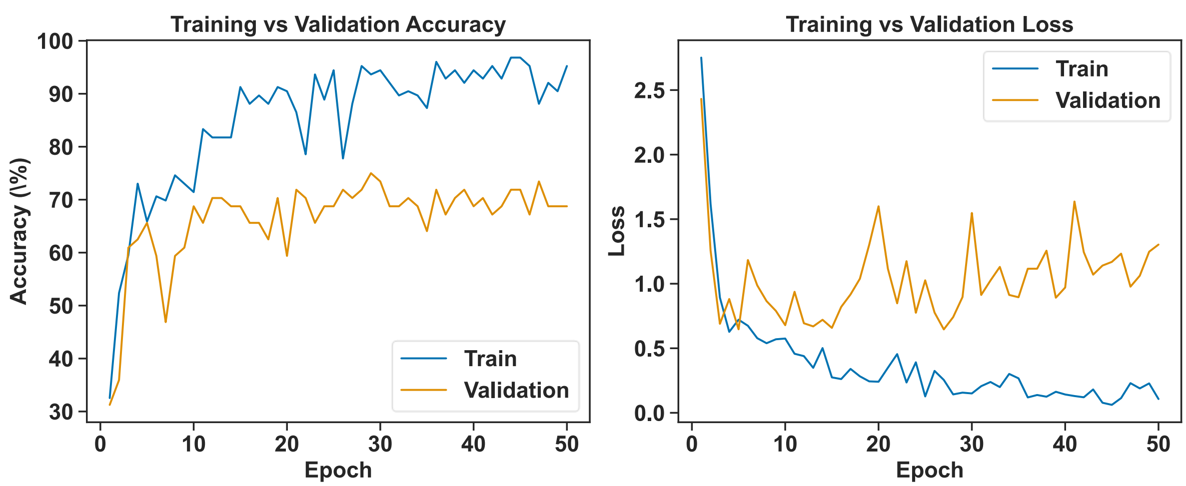

Figure 3.
BorneoNet training-validation performance

3.2. Benchmarking of Models

We evaluated six models: kNN, Naive Bayes, SVM, Random Forest, XGBoost, and our newly proposed model, BorneoNet. The evaluation was conducted using five key performance metrics: accuracy, precision, recall, F1-score, and Kappa. These metrics were utilized to assess the capability of each model in classifying palm fruit ripeness into three categories: ripe, half-ripe, and unripe. Further details on each metric are provided in Table 2.

The BorneoNet demonstrated the highest accuracy at 81.25%, indicating that it correctly classified the ripeness of palm fruits more frequently than the other models. SVM followed with 76.56% accuracy, which is also relatively high but significantly lower than that of BorneoNet. kNN and Random Forest both achieved a moderate accuracy of 62.50%. XGBoost slightly outperformed these models with

65.62% accuracy. Naive Bayes had the lowest accuracy at 37.50%, indicating significant limitations in its classification ability.

Table 2.
Benchmarking Metrics of Models.

Metric	kNN	Naïve Bayes	SVM	Random Forest	XGBoost	BorneoNet
Accuracy	62.50%	37.50%	76.56%	62.50%	65.62%	**81.25%**
Precision	61.42%	42.34%	77.28%	60.79%	63.46%	**81.82%**
Recall	61.19%	38.81%	74.24%	60.79%	63.69%	**78.99%**
F1-score	61.16%	36.71%	73.71%	60.51%	63.24%	**78.48%**
Kappa	0.4320	0.0886	0.6410	0.4309	0.4774	**0.7134**

Precision measures the proportion of correctly predicted positive observations (e.g., ripe fruit) to the total predicted positive observations. The BorneoNet again performed the best, with a precision of 81.82%. This indicates that the model consistently made correct predictions when identifying a specific class of fruit ripeness. The SVM also performed well, with a precision of 77.28%. XGBoost and kNN had moderately low precisions of 63.46% and 61.42%, respectively. Naive Bayes had poor precision (42.34%), reflecting its tendency to make incorrect predictions.

The recall (or sensitivity) indicates how well the model identifies each class of fruit ripeness. The BorneoNet had a recall of 78.99%, demonstrating its ability to correctly identify most instances of ripe, half-ripe, and unripe fruits. SVM followed closely with 74.24% recall. XGBoost and Random Forest both had recall values of approximately 63%, indicating a moderate ability to detect positive classes. Naive Bayes had the lowest recall at 38.81%, suggesting it struggled to identify a significant portion of the positive instances.

F1-Score is useful when there is an uneven class distribution, which could be the case for palm fruit ripeness. The BorneoNet had the highest F1-score of 78.48%, indicating that it effectively balanced precision and recall, providing robust predictions. The SVM followed with an F1-score of 73.71%, reflecting strong overall performance. XGBoost, kNN, and Random Forest had F1-scores between 61% and 63%, indicating moderate effectiveness. Naive Bayes had the lowest F1-score at 36.71%, demonstrating poor overall performance due to low precision and recall.

Kappa measures inter-rater agreement for categorical data. A higher kappa score indicates a stronger agreement between the model's predictions and the actual labels, beyond random chance. The BorneoNet had the highest kappa value of 0.7134, indicating a strong agreement between its predictions and the actual classifications of fruit ripeness. The SVM also showed strong agreement, with a kappa value of 0.6410. The XGBoost showed moderate agreement, with a kappa value of 0.4774. kNN and Random Forest both showed similar moderate performances, with kappa values of approximately 0.43. Naive Bayes had a very low kappa of 0.0886, reflecting almost no meaningful agreement between its predictions and actual fruit classifications.

The proposed BorneoNet consistently outperformed all other models in every metric. With an accuracy of 81.25%, precision of 81.82%, recall of 78.99%, and a high F1-score and kappa value, BorneoNet proved to be the most reliable model for classifying the ripeness of palm fruits. The performance gap between BorneoNet and the other models is particularly pronounced when compared to Naive Bayes, which struggles across all metrics with the lowest accuracy, precision, recall, and kappa.

3.3. McNemar Test

To further assess the differences in performance between BorneoNet and other models (kNN, Naive Bayes, SVM, Random Forest, and XGBoost), a McNemar test was conducted. The McNemar test is appropriate for comparing models that can only be evaluated once, particularly when dealing with paired nominal data rather than Gaussian data [36]. This test was used to compare the classification errors of two models and determine whether their performance differences were statistically significant.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 11: 1389-1401, 2025
DOI: 10.55214/2576-8484.v9i11.11220

It is especially useful when both models are tested on the same dataset, as it helps distinguish between differences due to random variation and genuine improvements.

This test results in a contingency table of classification outcomes between the first and second models and the p-value of whether the differences are statistically significant. Results show a p-value of 0.05 (5%), which was chosen as the cut-off for statistical significance. This result means that if the p-value is < 0.05, the difference between the performances is considered statistically significant.

Table 3.
Model Significance Test

Model Comparison	Contingency Table	P-value	Statistically Significant?
kNN vs BorneoNet	[[0, 0], [28, 36]]	7.45e-09	Yes
NaiveBayes vs BorneoNet	[[0, 0], [38, 26]]	7.28e-12	Yes
SVM vs BorneoNet	[[0, 0], [17, 47]]	1.53e-05	Yes
RandomForest vs BorneoNet	[[0, 0], [22, 42]]	4.77e-07	Yes
XGBoost vs BorneoNet	[[0, 0], [20, 44]]	1.91e-06	Yes

Table 3 presents a pairwise comparison of traditional machine learning models against the proposed BorneoNet. In all model comparisons, the McNemar test yielded p-values significantly lower than the 0.05 alpha level, indicating that the observed performance differences between BorneoNet and the other models (kNN, Naive Bayes, SVM, Random Forest, and XGBoost) are statistically significant.

This result confirms that the superior performance of BorneoNet across metrics is not due to random chance but represents a real improvement in the classification of palm fruit ripeness. This result suggests that BorneoNet is a more reliable and accurate model than traditional methods such as kNN, Naive Bayes, SVM, Random Forest, and XGBoost for this specific task.

3.4. Comparison with Previous Research

This section provides a benchmark between our previous research using the kNN classifier (k=1) [11] and the current study using the BorneoNet classifier. Our previous study used a dataset consisting of 100 palm fruit image samples. Table IV shows a significant improvement in model performance from the previous analysis to the current analysis. Accuracy increased from 0.6250 to 0.8000, indicating that the model correctly predicted more instances. Precision improved dramatically from 0.2525 to 0.7677, which means that the model now produces fewer false-positive errors. The recall increased from 0.2874 to 0.7444, suggesting that the model successfully identified more true positives. The F1-score also improved from 0.2688 to 0.7339, highlighting better overall classification effectiveness. Lastly, the Kappa score rose from 0.0099 to 0.6859, indicating a significant improvement in the agreement between the predicted and actual classes.

Table 4.
Comparison of Previous and Current Studies.

Previous study [11]		Current study
Accuracy	62.50%	80.00%
Precision	25.25%	76.77%
Recall	28.74%	74.44%
F1-score	26.88%	73.39%
Kappa	0.0099	0.6859

4. Conclusion

This study introduced BorneoNet as a compact convolutional model designed specifically for classifying palm fruit ripeness. The architecture focuses on a clear sequence of convolutional layers, batch normalization, and max-pooling, followed by two fully connected layers that provide a balanced level of abstraction. This configuration was selected to extract relevant visual cues without depending on deep or computationally expensive networks. The evaluation results show that this design is effective in learning the distinctions between unripe, half-ripe, and ripe fruit, even when working with images that vary in color intensity, lighting conditions, and fruit orientation.

The comparative analysis offers further insights into the strengths of this approach. In terms of accuracy, precision, recall, F1-score, and Kappa, BorneoNet consistently outperformed kNN, Naive Bayes, SVM, Random Forest, and XGBoost. These results were supported by the McNemar test, which confirmed that the differences were statistically significant rather than incidental. The findings suggest that a task-focused architecture can achieve reliable performance when designed around the dataset's characteristics. The model remained stable across different classes, indicating that the chosen structure is well-suited for datasets containing subtle differences in visual appearance.

Beyond its predictive performance, the lightweight nature of BorneoNet creates opportunities for practical use in plantation settings. Many agricultural applications rely on devices with limited computing power, and models with small computational requirements are more realistic for field operation. BorneoNet offers an example of how a streamlined architecture can support real-time classification without requiring large memory consumption or specialized hardware. Future work may extend this research by evaluating the model on a wider range of plantation environments, incorporating more diverse image conditions, and exploring its integration into field-ready systems for harvest monitoring. These steps will help advance the development of simple yet well-targeted models that support the growing needs of precision agriculture.

Funding:
This research was supported by a grant from the Hibah Penelitian Skema Fundamental–Reguler funded by the Directorate of Research, Technology, and Community Service (Direktorat Riset, Teknologi, dan Pengabdian kepada Masyarakat), Ministry of Higher Education, Science, and Technology of Indonesia.

Institutional Review Board Statement:
This study did not involve any human participants, personal data, or human-related interventions. The data used in this research consisted solely of photographic images of oil palm fruits collected in an open plantation environment. No identifiable or sensitive information was obtained, and no interaction with individuals occurred during the data acquisition process. As the research activities did not include experiments involving humans or animals, formal ethical approval from an Institutional Review Board was not required.

Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

References
[1] S. Saifullah, D. B. Prasetyo, R. Dreżewski, and F. A. Dwiyanto, "Palm oil maturity classification using K-nearest neighbors based on RGB and L* a* b color extraction," *Procedia Computer Science*, vol. 225, pp. 3011-3020, 2023. https://doi.org/10.1016/j.procs.2023.10.294

[2] H. Sastrohartono, A. P. Suryotomo, S. Saifullah, T. Suparyanto, A. S. Perbangsa, and B. Pardamean, "Drone application model for image acquisition of plantation areas and oil palm trees counting," presented at the 2022 International Conference on Information Management and Technology (ICIMTech), 2022.

[3] Z. Alamsyah, Y. Suandi Damayanti, R. O. Ulma, and E. Effran, "Optimization and business risk analysis on independent oil palm farming in Muara Tembesi District, batanghari regency," *Journal of Agri Socio Economics and Business*, vol. 5, no. 2, pp. 49–64, 2023. https://doi.org/10.31186/jaseb.5.2.49-64

[4] Y. Zhao, X. Zhu, Y. Hou, Y. Pan, L. Shi, and X. Li, "Effects of harvest maturity stage on postharvest quality of winter jujube (Zizyphus jujuba Mill. cv. Dongzao) fruit during cold storage," *Scientia Horticulturae*, vol. 277, p. 109778, 2021. https://doi.org/10.1016/j.scienta.2020.109778
[5] R. Lufu, A. Ambaw, and U. L. Opara, "Water loss of fresh fruit: Influencing pre-harvest, harvest and postharvest factors," *Scientia Horticulturae*, vol. 272, p. 109519, 2020. https://doi.org/10.1016/j.scienta.2020.109519
[6] T. Rhebergen *et al.*, "Closing yield gaps in oil palm production systems in Ghana through Best Management Practices," *European Journal of Agronomy*, vol. 115, p. 126011, 2020/04/01/ 2020. https://doi.org/10.1016/j.eja.2020.126011
[7] F. N. Maluin, M. Z. Hussein, and A. S. Idris, "An overview of the oil palm industry: Challenges and some emerging opportunities for nanotechnology development," *Agronomy*, vol. 10, no. 3, p. 356, 2020. https://doi.org/10.3390/agronomy10030356
[8] R. Sinambela, T. Mandang, I. D. M. Subrata, and W. Hermawan, "Application of an inductive sensor system for identifying ripeness and forecasting harvest time of oil palm," *Scientia Horticulturae*, vol. 265, p. 109231, 2020. https://doi.org/10.1016/j.scienta.2020.109231
[9] J. W. Lai, H. R. Ramli, L. I. Ismail, and W. Z. Wan Hasan, "Oil palm fresh fruit bunch ripeness detection methods: A systematic review," *Agriculture*, vol. 13, no. 1, p. 156, 2023. https://doi.org/10.3390/agriculture13010156
[10] H. A. Hasibuan, "Determination of yield, quality and chemical composition of palm oil and palm kernel oil from fresh fruit bunches of varying maturity as a basis for determining harvest maturity standards," *Jurnal Penelitian Kelapa Sawit*, vol. 28, no. 3, pp. 123-132, 2020. https://doi.org/10.22302/iopri.jur.jpks.v28i3.106
[11] K. Ragil and Nurahman, "Classification of palm fruit maturity level based on RGB and GLCM feature extraction using the K-NN algorithm," *Jurnal Ilmiah Komputasi*, vol. 22, no. 4, pp. 457-466, 2024. https://doi.org/10.32409/jikstik.22.4.3402
[12] K. Kipli *et al.*, "Deep learning applications for oil palm tree detection and counting," *Smart Agricultural Technology*, vol. 5, p. 100241, 2023. https://doi.org/10.1016/j.atech.2023.100241
[13] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. Cambridge, MA: MIT Press, 2016.
[14] D. W. Prabowo, H. A. Nugroho, N. A. Setiawan, and J. Debayle, "A systematic literature review of emotion recognition using EEG signals," *Cognitive Systems Research*, vol. 82, p. 101152, 2023. https://doi.org/10.1016/j.cogsys.2023.101152
[15] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, p. 53, 2021. https://doi.org/10.1186/s40537-021-00444-8
[16] D. Nasien, M. H. Adiya, I. Afrianty, M. Farkhan, and R. J. H. Butar-Butar, "Convolutional neural network model for sex determination using femur bones," *JOIV: International Journal on Informatics Visualization*, vol. 7, no. 4, pp. 2506-2512, 2023. http://dx.doi.org/10.62527/joiv.7.4.1711
[17] A. E. Minarno, M. Fadhlan, Y. Munarko, and D. R. Chandranegara, "Classification of dermoscopic images using CNN-SVM," *JOIV: International Journal on Informatics Visualization*, vol. 8, no. 2, pp. 606-612, 2024. http://dx.doi.org/10.62527/joiv.8.2.2153
[18] X. Zhao, L. Wang, Y. Zhang, X. Han, M. Deveci, and M. Parmar, "A review of convolutional neural networks in computer vision," *Artificial Intelligence Review*, vol. 57, p. 99, 2024. https://doi.org/10.1007/s10462-024-10721-6
[19] A. Taner, Y. B. Öztekin, and H. Duran, "Performance analysis of deep learning CNN models for variety classification in hazelnut," *Sustainability*, vol. 13, no. 12, p. 6527, 2021. https://doi.org/10.3390/su13126527
[20] A. A. Reshi *et al.*, "An efficient CNN model for COVID-19 disease detection based on x-ray image classification," *Complexity*, vol. 2021, no. 1, p. 6621607, 2021. https://doi.org/10.1155/2021/6621607
[21] T. Kattenborn, J. Leitloff, F. Schiefer, and S. Hinz, "Review on Convolutional Neural Networks (CNN) in vegetation remote sensing," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 173, pp. 24-49, 2021. https://doi.org/10.1016/j.isprsjprs.2020.12.010
[22] G. T. H. Tzuan, F. H. Hashim, T. Raj, A. Baseri Huddin, and M. S. Sajab, "Oil palm fruits ripeness classification based on the characteristics of protein, lipid, carotene, and guanine/cytosine from the Raman spectra," *Plants*, vol. 11, no. 15, p. 1936, 2022. https://doi.org/10.3390/plants11151936
[23] C. Unigarro, J. Hernandez, and H. Florez, "Artificial neural networks for image processing in precision agriculture: A systematic literature review on mango, apple, lemon, and coffee crops," *Informatics*, vol. 12, no. 2, p. 46, 2025. https://doi.org/10.3390/informatics12020046
[24] X. Guo *et al.*, "LWheatNet: A lightweight convolutional neural network with mixed attention mechanism for wheat seed classification," *Frontiers in Plant Science*, vol. 15, p. 1509656, 2025. https://doi.org/10.3389/fpls.2024.1509656
[25] D. W. Prabowo, H. A. Nugroho, N. A. Setiawan, and J. Debayle, "An advanced data augmentation scheme on limited EEG signals for human emotion recognition," in *Proceeding of the 3rd International Conference on Electronics, Biomedical Engineering, and Health Informatics: ICEBEHI 2022, 5–6 October, Surabaya, Indonesia (pp. 391-409). Singapore: Springer Nature Singapore*, 2023.
[26] D. W. Prabowo, N. A. Setiawan, J. Debayle, and H. A. Nugroho, "Enhancing EEG-based emotion recognition using asymmetric windowing recurrence plots," *IEEE Access*, vol. 12, pp. 85969-85982, 2024. https://doi.org/10.1109/ACCESS.2024.3409384

[27] A. Sumayli, "Development of advanced machine learning models for optimization of methyl ester biofuel production from papaya oil: Gaussian process regression (GPR), multilayer perceptron (MLP), and K-nearest neighbor (KNN) regression models," *Arabian Journal of Chemistry*, vol. 16, no. 7, p. 104833, 2023. https://doi.org/10.1016/j.arabjc.2023.104833

[28] A. Hudon, M. Beaudoin, K. Phraxayavong, L. Dellazizzo, S. Potvin, and A. Dumais, "Use of automated thematic annotations for small data sets in a psychotherapeutic context: Systematic review of machine learning algorithms," *JMIR Mental Health*, vol. 8, no. 10, p. e22651, 2021. https://doi.org/10.2196/22651

[29] M. Aqeel, A. Sohaib, M. Iqbal, H. U. Rehman, and F. Rustam, "Hyperspectral identification of oil adulteration using machine learning techniques," *Current Research in Food Science*, vol. 8, p. 100773, 2024. https://doi.org/10.1016/j.crfs.2024.100773

[30] Y. Shang, "Prevention and detection of DDOS attack in virtual cloud computing environment using Naive Bayes algorithm of machine learning," *Measurement: Sensors*, vol. 31, p. 100991, 2024. https://doi.org/10.1016/j.measen.2023.100991

[31] P. B. Yang, Y. J. Chan, S. K. Yazdi, and J. W. Lim, "Optimisation and economic analysis of industrial-scale anaerobic co-digestion (ACoD) of palm oil mill effluent (POME) and decanter cake (DC) using machine learning models: A comparative study of Gradient Boosting Machines (GBM), K-nearest neighbours (KNN), and random forest (RF)," *Journal of Water Process Engineering*, vol. 58, p. 104752, 2024. https://doi.org/10.1016/j.jwpe.2023.104752

[32] Z. Jin, J. Shang, Q. Zhu, C. Ling, W. Xie, and B. Qiang, "RFRSF: Employee turnover prediction based on random forests and survival analysis," in *In International Conference on Web Information Systems Engineering (pp. 503-515). Cham: Springer International Publishing*, 2020.

[33] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273-297, 1995. https://doi.org/10.1007/BF00994018

[34] I. H. Witten, E. Frank, and M. A. Hall, *Data mining: Practical machine learning tools and techniques*, 3rd ed. Burlington, MA: Morgan Kaufmann Publishers, 2011.

[35] T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," in *Proceedings of the 22nd ACM Sigkdd International Conference on Knowledge Discovery and Data Mining*, 2016.

[36] A. Y. Al Hammadi *et al.*, "Explainable artificial intelligence to evaluate industrial internal security using EEG signals in IoT framework," *Ad Hoc Networks*, vol. 123, p. 102641, 2021. https://doi.org/10.1016/j.adhoc.2021.102641

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 11: 1389-1401, 2025
DOI: 10.55214/2576-8484.v9i11.11220