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Performance comparison of machine learning algorithms for ikat weaving classification

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Abstract
Ikat weaving is a rich traditional heritage of Kota Kediri, Indonesia, with a diverse array of intricate motifs that reflect the cultural richness of the region. As new motifs emerge and information about older designs fades, manual identification becomes time-consuming and difficult. This study leverages machine learning technology, specifically XGBoost, Random Forest, and Neural Network algorithms, to automate the classification of these weaving patterns. The dataset consisted of 600 images, split into 480 images (80%) for training and 120 images (20%) for testing, representing four distinct weaving motifs: "Gumul Weaving, Bolleches Weaving, Kuda Kepang Weaving, and Sekar Jagad Weaving." The study achieves high accuracy, with precision, recall, and F1-score all reaching 100%, underscoring its potential to not only improve the efficiency of motif identification, but also play a crucial role in preserving and promoting Indonesia's cultural heritage. Future research should focus on further optimizing these algorithms and expanding datasets to capture a broader range of ikat motifs. Additionally, enhancing the application of this model can contribute to a deeper understanding and broader appreciation of Kota Kediri's cultural wealth through digital platforms.

1. Introduction

Ikat weaving is a traditional Indonesian craft that has flourished in East Java, particularly in Bandar Kidul, Kota Kediri, where this cottage industry has been passed down through generations since the Dutch colonial era. Ikat fabric can be categorized as a safeguard for artistic creations similar to batik, protecting its motifs, designs, and color compositions, representing Indonesia's cultural heritage that continues to evolve. It is crucial to inventory and identify the distinctive ikat weavings of Kediri to avoid confusion between newly created motifs attributed to known creators and older motifs whose origins are no longer known. This prevents new creations from falling into the public domain, even when their creators are known and their aesthetics are clear. Ikat weaving exhibits a diverse range of intricate motifs and variations. Manual identification is often challenging and time-consuming, especially for those without deep knowledge of these patterns. Machine learning technology offers sophisticated solutions for pattern identification and classification [1], [2]. With adequate datasets, machine learning models can be trained to recognize complex patterns with high accuracy [3], [4], [5]. Such recognition systems can serve as educational tools to enhance public knowledge about ikat weaving, applicable in various educational and training programs for both general public and students. Developing a prototype of ikat recognition system based on machine learning is an initial step to test the effectiveness and utility of this technology, laying the groundwork for more advanced systems in the future [6], [7], [8].

Many researchers have applied machine learning to identify motif patterns in woven fabric images. Adri Gabriel et al. [9] proposed an approach using decision trees as classifiers combined with SqueezeNet for feature extraction to recognize pictures of typical woven fabrics from East Nusa Tenggara. Its effectiveness in high-dimensional data classification makes it a valuable tool for modeling unique patterns found in woven fabric images. The dataset used includes various types of East Nusa Tenggara woven fabrics, with experimental results showing promising success rates in classifying complex motifs and patterns, achieving 92.9% accuracy. Another study by Etike et al. [10] applied an artificial intelligence using CNN to process images of Lotis woven fabrics from South East Sulawesi, known for their unique patterns, motifs, and colors. CNN has proven highly effective in classifying and identifying image patterns, including color recognition [11]. The dataset comprised 50 images divided into 20 for training, 10 for validation, and 20 for testing. The research resulted in an accuracy of 98.02%, with an average of 97.56% and a system accuracy of 96.64%. In another study, Yoze et al. [12] conducted a recognition and classification of Malay woven motifs using Faster R-CNN with VGG architecture, measuring accuracy, precision, and recall using K-fold Cross-validation. Faster R-CNN is one of the methods used for object recognition in digital images [13]. The dataset consisted of 100 images shuffled into 5 folds. The data was split into 80 training and 20 testing samples. The research achieved an accuracy of 82.14%, precision of 91.38%, and recall of 91.36%. Mukhlis et al. [14] focused on recognizing the motifs of Malay woven fabrics, which exhibit significant diversity, making it challenging to differentiate. CNN was employed using a dataset from Ma

Bengkalis princess woven fabrics, consisting of 1000 motif images, divided into 80% training and 20% testing samples. The dataset was categorized into three motifs: Pucuk Rebung, Awan Siku, and Keluang Siku. The model achieved an accuracy of 95% with 15 epochs. Rusda et al. [15] used CNN to identify bumpak woven fabric motifs, achieving an accuracy of 98%. Using CNN with ResNet50, Theresia et al. [16] obtained an accuracy of 90.96%, recall of 90.96%, precision of 90.60%, and F1-score of 90.68% in recognizing motifs of Bali endek fabrics. Utilizing CNN for ikat fabric motif classification promises stronger and more accurate results.

In this research, machine learning methods were employed to determine the best-performing model for classifying intricate ikat weaving patterns. The proposed models included XGBoost, Random Forest, and Neural Networks. These algorithms were selected based on their effectiveness in handling complex, high-dimensional data and their proven track record in classification tasks. XGBoost is known for its strong performance in handling large datasets with high accuracy, while Random Forest provides robustness through ensemble learning, and Neural Networks excel at capturing non-linear relationships in data. By comparing these models, the study aimed to identify which approach provides the highest accuracy and reliability in recognizing and categorizing the diverse motifs of Kediri's ikat weavings. Each model was trained and tested using specific parameters and hyperparameters, and their performances were assessed through various metrics, including accuracy, precision, recall, and F1-score. The dataset used for this research consisted of 600 images, split into 480 images (80%) for training and 120 images (20%) for testing.

The structure of this paper is organized as follows: Part 1 provides an introduction, including problem analysis, proposed solutions, and relevant literature review. This section discusses the challenges faced by general public in identifying various types of ikat fabric motifs and proposes solutions using deep learning-based machine learning approaches. Part 2 details the research methodology, dataset preparation, model architecture, and experimental setup used in this study. Part 3 presents the results and discussion, where the performance of the proposed models were analyzed through various evaluation metrics. Finally, Part 4 concludes the paper, summarizing findings and suggesting potential future work in this field.

2. Research Method

The research started by collecting ikat woven image data from various sources, followed by a pre-processing stage to improve image quality through contrast enhancement, noise removal, and normalization. After completing the pre-processing, the dataset was partitioned, where 80% allocated for training and 20% for testing. The training data was used to train several machine learning models such as XGBoost, random forest, and neural networks. After the training process, the performance of each model was evaluated using metrics such as accuracy, precision, recall, and F1-score. The model with the best performance is selected for the final classification, ensuring the most accurate and reliable results. Flow of proposed scheme can be seen in Figure 1.

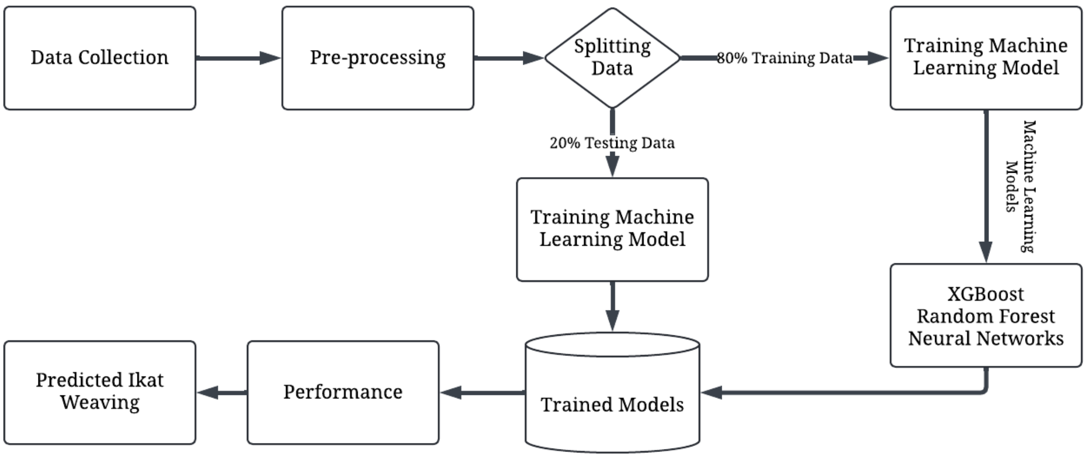
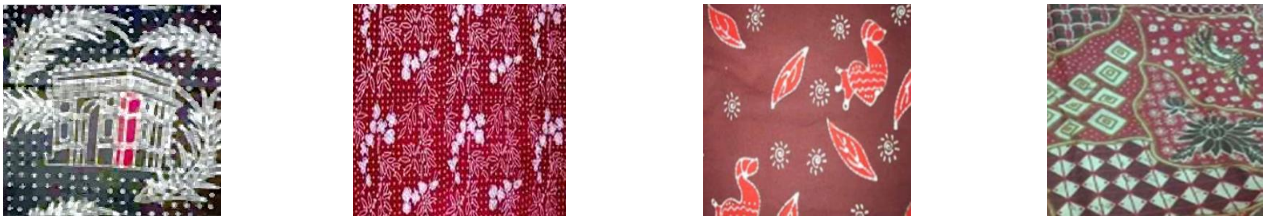


Figure 1. Proposed Scheme

2.1 Data Collection

The data were collceted from public sources with random image sizes. Furthermore, a pre-processing stage was carried out to produce a perfect dataset image suitable for training. This pre-processing stage included contrast enhancement, noise removal, and image normalization. The sample dataset, as depicted in Figure 2, consisted of 600 images, with 150 images per class, representing four classes: "Gumul Weaving, Bolleches Weaving, Kuda Kepang Weaving, and Sekar Jagad Weaving." The sample dataset in Figure 2 has not gone through the pre-processing stage, so the images appear blurry and lack the clarity and detail needed for further analysis. The dataset was then split into 480 images (80%) for training and 120 images (20%) for testing.



(a) Gumul Weaving (b) Bolleches Weaving (c) Kuda Kepang Weaving (d) Sekar Jagad Weaving

Figure 2. Sample Datasets

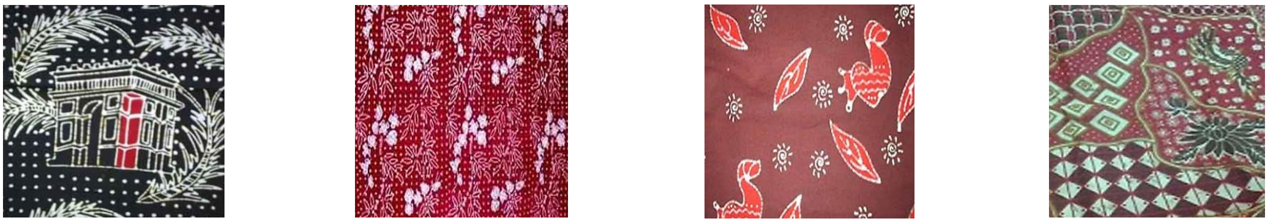
2.2 Pre-processing

The pre-processing stage employed a median filter to reduce noise and enhance image sharpness, utilizing a 3x3 window size to compute the median value for each pixel based on its neighboring pixels [17], [18]. Subsequently, the images were resized from random sizes to 512 x 512 x 3 to ensure consistency for the training phase of the model. This resizing step is crucial for maintaining similar dimensions across all images, thereby enhancing the performance and efficiency of the machine learning model. In mathematical terms, the median filter operation for a pixel (i, j) in a specific color channel c is defined as Equation 1, while Equation 2 represents the equation for changing pixel values which can be called the resize process.

$$filteredImage(i, j, c) = median(histeqImage(i-1{:}\,i+1, j-1{:}\,j+1, c)) \quad (1)$$

Where, $median$ computes the median value of the pixel values within the 3x3 neighborhood of $histeqImage$. This operation was repeated for each color channel to maintain color information integrity throughout the process. Where, $\delta_x = x\ /scale\_factor\_x - \lfloor x/scale\_factor\_x \rfloor$ and $\delta_y = y\ /scale\_factor\_y - \lfloor y/scale\_factor\_y \rfloor$ are interpolation actors for each dimension. Results of pre-processing can be seen in Figure 3.

$$\begin{aligned} I_{resized} = (x, y, :) = {} & (1-\delta_x)(1-\delta_y) I_{randomsize}\left(\left\lfloor \frac{x}{scale_{factor_x}} \right\rfloor, \left\lfloor \frac{y}{scale_{factor_y}} \right\rfloor, :\right) \\ & + \delta_x (1-\delta_y) I_{randomsize}\left(\left\lfloor \frac{x}{scale_{factor_x}} \right\rfloor, \left\lfloor \frac{y}{scale_{factor_y}} \right\rfloor, :\right) \\ & + (1-\delta_x)\delta_y I_{randomsize}\left(\left\lfloor \frac{x}{scale_{factor_x}} \right\rfloor, \left\lfloor \frac{y}{scale_{factor_y}} \right\rfloor, :\right) \\ & + \delta_x \delta_y I_{randomsize}\left(\left\lfloor \frac{x}{scale_{factor_x}} \right\rfloor, \left\lfloor \frac{y}{scale_{factor_y}} \right\rfloor, :\right) \end{aligned} \quad (2)$$



(a) Gumul Weaving (b) Bolleches Weaving (c) Kuda Kepang Weaving (d) Sekar Jagad Weaving

Figure 3. Sample Datasets after Pre-processing

Figure 2 displays the sample dataset before undergoing any pre-processing, where the images appear blurry and lack the necessary clarity and detail for further analysis. In contrast, Figure 3 presents the same images after the pre-processing stage, which includes noise removal, contrast enhancement, and resizing. As a result, the images in Figure 3 show improved clarity and consistency, making them suitable for training the machine learning models. This distinction between the raw dataset in Figure 2 and the processed images in Figure 3 highlights the effectiveness of the pre-processing stage in enhancing image quality.

2.3 Machine Learning Models

XGBoost or Extreme Gradient Boosting is widely recognized as a potent machine learning algorithm known for its efficacy in classification assignments such as identifying traditional ikat weaving patterns in Kediri [19], [20]. Utilizing an ensemble of weak learners, XGBoost sequentially builds decision trees to correct errors from previous models, thereby enhancing predictive accuracy. Unlike traditional decision tree methods, XGBoost applies a gradient boosting framework that optimizes the model's performance iteratively, refining predictions through each sequential tree addition. This approach minimizes overfitting by penalizing complexity, ensuring robust classification results for intricate and diverse ikat motifs.

Random forest is a robust ensemble learning technique, plays a pivotal role in classifying the intricate ikat weaving patterns found in Kediri [21]. This method constructs multiple decision trees using bootstrapped subsets of the training data and random feature selection, fostering model diversity and reducing variance [22]. Each decision tree independently contributes to the final prediction through a voting mechanism, thereby enhancing classification accuracy. Unlike traditional methods that may suffer from high bias or variance, Random Forest leverages the wisdom of crowds, ensuring robust performance across various ikat motifs by aggregating predictions from multiple trees.

Meanwhile, the neural networks offer a sophisticated approach to classifying the intricate ikat weaving patterns prevalent in Kediri, leveraging layers of interconnected nodes inspired by biological neurons [23], [24]. This deep learning technique learns hierarchical representations of data, capturing intricate patterns and relationships in ikat motifs. Through forward and backward propagation, neural networks optimize model parameters, adjusting weights to minimize prediction errors [25], [26]. Unlike traditional algorithms, neural networks excel in capturing nonlinear relationships and intricate dependencies within the data, making them well-suited for discerning subtle variations in Kediri's diverse ikat designs.

Through distinct training methodologies, the three chosen models—XGBoost, Random Forest, and Neural Networks—have been optimized to classify intricate ikat weaving patterns depicted in Figure 4. Each model capitalizes their unique strengths, namely XGBoost refines predictions iteratively using gradient boosting, adeptly handling complex patterns; Random Forest aggregates decisions from diverse decision trees through ensemble learning, ensuring robustness against variance; and Neural Networks employ deep learning's hierarchical feature extraction to discern subtle variations within Kediri's diverse ikat designs. These models collectively provide a comprehensive approach to pattern classification, each offering specific advantages suited to the intricacies observed in weaving motifs.

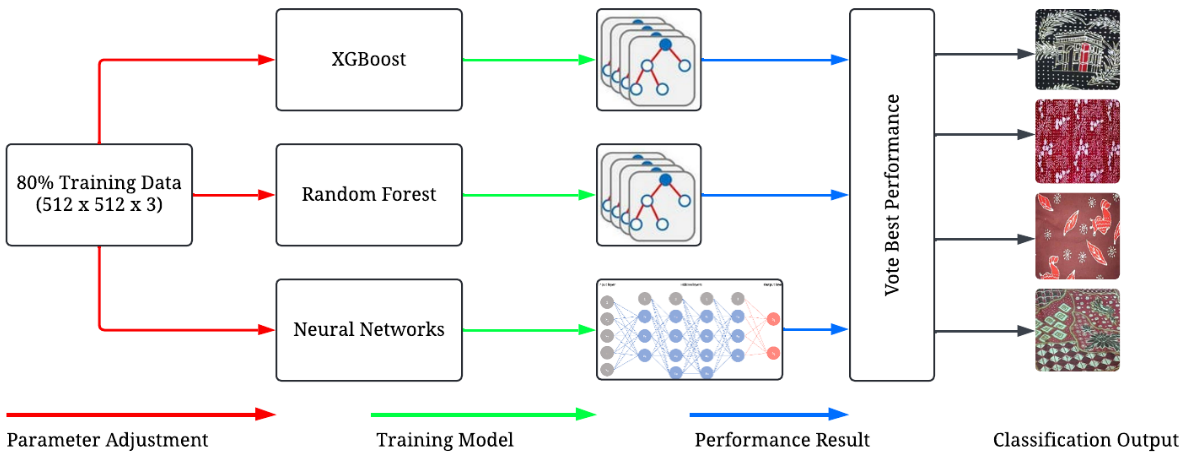


Figure 4. Training Models

3. Results and Discussion

The model was trained using Python on a system with hardware specifications, including a Ryzen 7 7800X3D processor, a 3070 TI graphics card, and 32 GB of RAM. The model training was evaluated using a confusion matrix table to assess the performance of ikat weaving pattern classification. The confusion matrix shows the count of accurate and inaccurate predictions for each class, providing insight into the accuracy and weaknesses of the model in identifying various ikat motifs. In addition, a training graph is used to visualize the changes in loss and accuracy values during the training process. This graph allows for monitoring the progress of the model from epoch to epoch, as well as identifying whether the model is overfitting or underfitting, allowing for necessary parameter adjustments to improve overall performance. The training process involved the use of detailed parameters and hyperparameters as listed in Table 1.

Table 1. Parameter Per Model During Training

XGBoost	Random Forest	Neural Networks
Learning Rate: 0.1	Min Samples Split: 2	Learning Rate: 0.0001
Max Depth: 6	Max Depth: 10	Number of Epochs: 20
Subsample: 0.8	Min Samples Leaf: 1	Batch Size: 32
Colsample by Tree: 0.8	Max Features: sqrt	Hidden Layers: 2 layers
Number of Estimators: 100	Number of Estimators: 100	with 128 units each

The training outcomes were assessed based on the predetermined parameters outlined in Table 1. The performance of each model was explained in their respective subsections, where Section 3.1 represents XGBoost Performance, Section 3.2 delineates Random Forest Performance, and Section 3.3 outlines Neural Networks Performance The evaluation performance can be seen in Equations 3–6. This analysis encompasses metrics such as accuracy, precision, recall, and F1-score for each model, interpreted through confusion matrices to evaluate their efficacy in accurately classifying intricate ikat weaving patterns.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

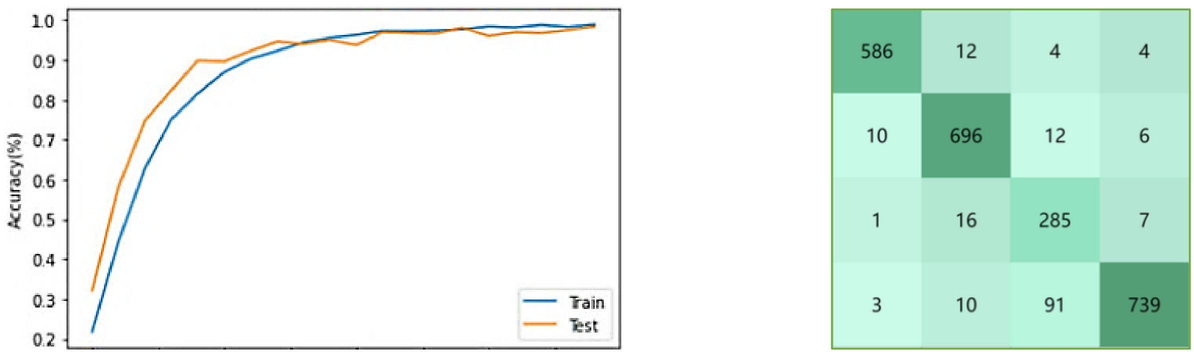
$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision \times Recall} \tag{6}$$

3.1 XGBoost Performance

The training graph and confusion matrix table results using the XGBoost model can be observed in Figure 5. Additionally, the evaluation results based on the confusion matrix are presented in Table 2.



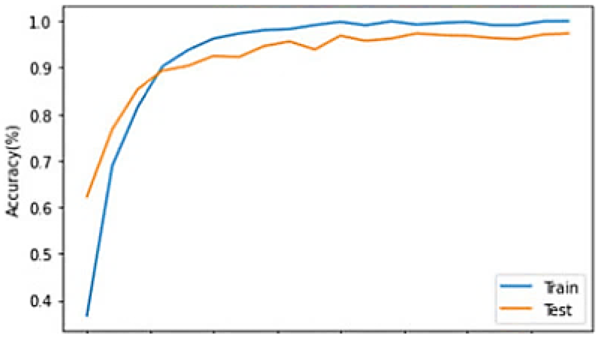
(a) Training graph (b) Table of confusion matrix

Figure 5. Performance of XGBoost Models

From Figure 5, it can be seen that the results obtained using the XGBoost model with the parameters Learning Rate: 0.1, Max Depth: 6, Subsample: 0.8, Colsample by Tree: 0.8, and Number of Estimators: 100, yielded an accuracy of 98.88%. Figure 5(a) shows the training graph for the XGBoost model, where the accuracy increases steadily over the epochs, indicating that the model is learning effectively from the training data. The loss graph (Figure 5(b)) exhibits a gradual decrease, suggesting that the model is minimizing the errors and improving over time. This consistent improvement in both accuracy and loss demonstrates that XGBoost is not overfitting, as both metrics are converging smoothly.

3.2 Random Forest Performance

The training graph and confusion matrix table results using the random forest model can be observed in Figure 6. Additionally, the evaluation results based on the confusion matrix are presented in Table 2.



(a) Training graph

553	28	12	8
32	637	28	10
5	46	253	18
10	23	17	720

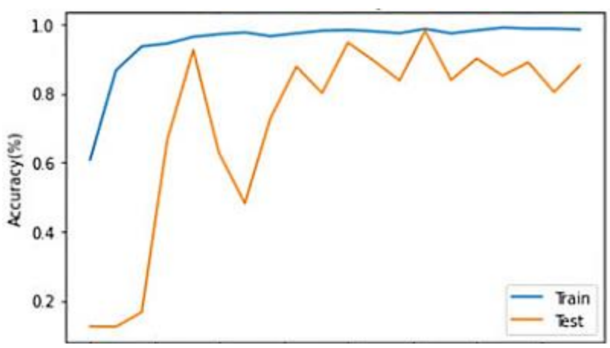
(b) Table of confusion matrix

Figure 6. Performance of Random Forest Models

The results obtained using the Random Forest model with the parameters Min Samples Split: 2, Max Depth: 10, Min Samples Leaf: 1, Max Features: sqrt, and Number of Estimators: 100, yielded an accuracy of 94.16%. Figure 6(a) presents the training graph for the Random Forest model, with accuracy steadily improving through the training process, though slightly slower compared to XGBoost. The loss graph (Figure 6(b)) shows a steady decline, indicating that the model is also learning and improving. The Random Forest model's performance is strong, but the accuracy is not as high as XGBoost, which is reflected in the model's slightly lower accuracy and F1-score in the overall performance analysis.

3.3 Neural Networks Performance

The training graph and confusion matrix table results using the neural networks model can be observed in Figure 7. Additionally, the evaluation results based on the confusion matrix are presented in Table 2.



(a) Training graph

523	58	12	10
56	577	38	12
8	65	245	16
13	34	15	718

(b) Table of confusion matrix

Figure 7. Performance of Neural Networks Models

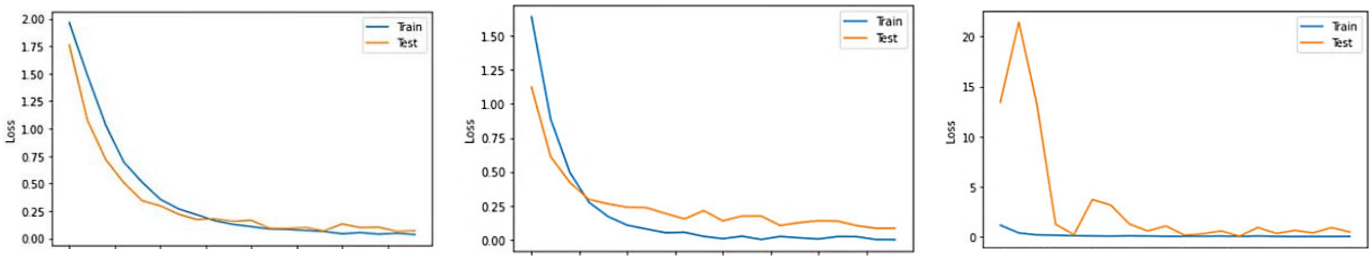
The results obtained using the Neural Networks model with the parameters Learning Rate: 0.0001, Number of Epochs: 20, Batch Size: 32, and Hidden Layers: 2 layers with 128 units each, yielded an accuracy of 89.22%. Figure 7(a) shows the training graph for the Neural Networks model, where the accuracy increases initially, but then levels off or fluctuates. This pattern could suggest that the model is beginning to overfit, as the training accuracy continues to improve while the testing accuracy remains stagnant. The loss graph (Figure 7(b)) also shows similar pattern, with a decline in training loss or a plateau and increase in validation loss after a certain point. This indicates that the model may have learned the training data too well, failing to generalize effectively to unseen data, which is a typical sign of overfitting.

Table 2. Performance Analysis

Model	Accuracy	Precision	Recall	F1-Score
XGBoost	98.88%	100%	100%	100%
Random Forest	94.16%	96%	95%	94%
Neural Networks	89.22%	90%	90%	90%

Table 2 presents the performance of three models—XGBoost, Random Forest, and Neural Network—based on four evaluation metrics: accuracy, precision, recall, and F1-score. XGBoost outperforms the other models in all metrics, achieving an accuracy of 98.88%, precision of 100%, recall of 100%, and an F1-score of 100%, making it the best-performing model. Random Forest achieved an accuracy of 94.16%, with precision of 96%, recall of 95%, and an F1-score of 94%, while Neural Network recorded the lowest accuracy at 89.22%, with precision, recall, and F1-score of 90% each. The selection of the best model is based on a weighted average approach, where XGBoost consistently excels across all metrics, making it the optimal choice for classifying ikat weaving patterns.

The models mentioned above also underwent a loss graph analysis, as depicted in Figure 8. The loss graph is essential for understanding how well each model is learning over time. By plotting the loss values against the number of iterations or epochs, we can observe the convergence behavior of the models. A decreasing loss indicates that the model is effectively learning from the data, while a stable or increasing loss can signal potential issues such as overfitting or underfitting.



(a) Loss graph of XGBoost model

(b) Loss graph of random forest model

(c) Loss graph of neural networks model

Figure 8. A Comparison Graph Model

4. Conclusion

This study introduces a novel approach using several machine learning algorithms such as XGBoost, Random Forest, and neural networks, which significantly enhance the classification of traditional Indonesian ikat weaving motifs. Among the proposed methods, XGBoost achieved the highest accuracy at 98.88%, with precision, recall, and F1-score all at 100%. Random Forest attained an accuracy of 94.16% with a precision of 96%, recall of 95%, and an F1-score of 94%, while the Neural Network achieved an accuracy of 89.22% with precision, recall, and F1-score all reaching 90%. This advancement holds great potential for cultural preservation and educational purposes, aiding society in better understanding and appreciating traditional Indonesian ikat weaving through accurate digital classification. For future research, efforts should focus on reducing the levels of overfitting and underfitting by adjusting parameters and incorporating additional layers into the models. Fine-tuning hyperparameters such as the learning rate, batch size, and the number of estimators or epochs can significantly enhance model performance and generalization. Furthermore, experimenting with the architecture of neural networks, including increasing the number of hidden layers and units, could improve the ability to capture complex patterns in the data. These adjustments will help create more robust models capable of accurately classifying intricate ikat weaving patterns in diverse and challenging datasets.

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