TRANSFORMING WOVEN IKAT FABRIC: ADVANCED CLASSIFICATION VIA TRANSFER LEARNING AND CONVOLUTIONAL NEURAL NETWORKS

Silvester Tena[1], Bernadectus Yudi Dwiandiyanta [2]

[1]Electrical Engineering Department, Science and Engineering Faculty, University of Nusa Cendana, Kupang, Indonesia
[2]Department of Informatics, Faculty of Industrial Technology, Universitas Atma Jaya Yogyakarta, Yogyakarta, Indonesia
Email: siltena@staf.undana.ac.id, yudi.dwiandiyanta@uajy.ac.id

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ABSTRACT

The woven ikat fabric from Nusa Tenggara Timur is a local wisdom that must be preserved. Due to its vast array of motifs, users often encounter challenges in its recognition. For this study, the TenunIkatNet dataset was employed. One prominent recognition method involves classification based on the motif type and geographical origin. The efficacy of the classification is heavily contingent upon the method of extraction employed. The Convolutional Neural Network (CNN) method is used for feature extraction and classification processes. This research compares the classification performance of the VGG16 baseline model and the proposed model. The proposed model modifies the baseline at the fully connected layer and the training process from the first convolution layer. Training the model from the early convolution layer aims to adjust the network weights as input to the output layer due to the different dataset characteristics. Incorporating elements such as Global Average Pooling (GAP), Batch Bormalization (BN), and Dropout have proven instrumental in mitigating overfitting. The transfer learning strategy is used for feature extraction and classification because the model has been intelligently trained on a large dataset. The research findings unequivocally indicate that the performance of the modified model supersedes that of the baseline model. Based on the evaluation metrics, the proposed model is superior to the baseline model with precision, recall, accuracy, and F1-score, respectively 98.73%, 98.54%, 98.54%, and 98.53%.

Keywords: *woven ikat fabric, classification, CNN, transfer learning*

Corresponding Author:
Silvester Tena,
Electrical Engineering Department, Science and Engineering Faculty University of Nusa Cendana,
Jl. Adisucipto, Penfui, Kupang
siltena@staf.undana.ac.id

1. INTRODUCTION

Indonesia has a variety of local wisdom in the form of traditional fabrics such as batik, songket, and woven ikat. Notably, the woven ikat fabric is a testament to the cultural wealth of Nusa Tenggara Timur (NTT). This fabric emerges from intricate weaving techniques employed by the indigenous people of NTT. It is meticulously crafted from strands of weft or warp yarn pre-emptively bound and immersed in natural dyes. The distinguishing attributes of woven ikat are encapsulated in its foundational materials, the method of fabrication, the dyeing process, and the intricate motifs it features. Woven ikat fabric has various motifs under the diverse culture of the Nusa Tenggara Timur community. The inspiration for these motifs often stems from variables such as the fabric's geographical provenance, its region's demographics, and the community's socio-cultural fabric.

Consequently, the motifs of the woven ikat fabrics exhibit regional nuances, mirroring the ethos and lifestyle of their respective communities. Each region's distinct cultural backdrop contributes unique patterns and ornamental designs to the woven ikat repertoire. For instance, the Sumba region is renowned for its weaves adorned with animal motifs, while Rote is characterized by its leaf motifs. On the other hand, Alor's signature woven fabric is distinguished by the warp ikat technique, and its hues are derived from organic sources, encompassing both flora and marine life, such as squid, sea cucumbers, and seaweed [1]. The woven ikat from the Timor region is distinctively characterized by animal motifs, often bordered by narrow pathways, and is further accentuated by vivid geometric patterns [2]. The increasing diversity in woven ikat motifs, attributed to various modifications, poses recognition challenges for users. Nonetheless, these modifications do not obscure the distinctive characteristics associated with specific regions. Many users grapple with differentiating between the intricate motifs of ikat fabric and their corresponding regions of origin. Insufficient foundational knowledge among users can lead to a diminished appreciation for local wisdom. In contemporary times, there is a pressing need for an electronic knowledge base to facilitate the recognition of distinct ikat fabric motifs. Based on the visual similarities inherent in woven ikat fabric images, classification is a prominent recognition method. Many studies on classifying woven fabrics and batik have established benchmarks for feature extraction methodologies. The efficacy of recognizing specific motif types is intrinsically tied to the feature extraction method deployed. Prior research has leveraged the transfer learning paradigm, particularly for pretrained models. One such pretrained Convolutional Neural Network (CNN) model, acclaimed for its state-of-the-art performance, is VGG16 [3]. Empirical evidence suggests that the VGG16 pretrained model consistently delivers superior performance [4], [5], [6], [7], [8]. The predilection for the transfer learning strategy arises from constraints associated with training data availability and computational efficiency considerations.

Distinct research endeavors have explored the classification and recognition of ikat fabrics, employing the Grey Level Co-occurrence Matrix (GLCM) and Color Co-occurrence Matrix (CCM) methods for texture and color feature extraction [9]. Further studies have sought to juxtapose various feature extraction techniques in the realm of ikat image classification, encompassing edge detection, wavelets, and histograms [10]. The recognition of woven ikat fabric images is anchored in features extracted through the Speeded Up Robust Features (SURF) methodology [11]. Another noteworthy study by [9] delved into the classification of ikat fabrics, achieving an accuracy metric of 80% across four distinct classes. A cursory review of prior research reveals that several studies have reported accuracy rates below the 90% threshold and often grapple with dataset limitations. Given the unique characteristics of ikat woven fabric images, it is imperative to deploy feature extraction techniques adept at handling nuances in texture, color, shape, and spatial information.

In the present study, we introduce a model that diverges from the traditional baseline and is tailored to resonate with the image characteristics endemic to NTT woven ikat fabrics. The VGG16 model, grounded in CNN architecture and heralded as the benchmark in prior research [3], [6]. serves as the foundational baseline for this study. A comprehensive review of relevant literature underscores the preeminence of the CNN method as a feature extractor, especially when juxtaposed against handcrafted techniques, and this is particularly salient for expansive datasets [12].

This research will classify types of woven ikat fabric motifs using transfer learning techniques for the baseline model and modification of the VGG16 model. The classification of woven ikat fabrics serves as a foundational knowledge base for identifying various motifs and their respective regions of origin, facilitating easier recognition for end-users. Such identification of woven fabric motifs plays a pivotal role in preserving local

wisdom, documenting traditional crafts, and promoting cultural heritage. Modifications to the VGG16 architecture are implemented primarily in the fully connected layer (FCL). Specifically, Global Average Pooling (GAP), Batch Normalization (BN), and Dropout layers are integrated into the FCL. These additions mitigate the issue of overfitting, particularly in scenarios with limited dataset size. Furthermore, a dense layer is incorporated to tailor the network to the specific number of classes present in the dataset.
The structure of this paper is methodical, with section 2 elucidating the materials and methodologies deployed. Section 3 delves into the empirical findings, discussions, and avenues for future research. The paper culminates with conclusions presented in the final section.

2. MATERIALS AND METHODS

2.1 TenunIkatNet Dataset

In this study, the utilized ikat fabric dataset comprises 120 distinct classes. Each class encapsulates 40 images, culminating in a total of 4,800 images. These images possess dimensions of 256 x 256 pixels. An augmentation process is carried out to increase the amount of training data. The augmentation process is carried out on the training data. The augmentation techniques deployed include zooming, rotation, flipping, and shear range adjustments. The dataset was systematically partitioned into training, validation, and testing subsets, with allocations of 80%, 10%, and 10%, respectively. The source of the dataset can be accessed via the provided link https://github.com/siltena2023/TenunIkatNet.

Figure 1. Several samples of woven ikat fabrics.

2.2 Research Framework

The research framework is delineated in a block diagram, as depicted in Figure 2. During the image pre-processing phase, image data is adjusted to be compatible as input for the designated feature extraction model. The model subjected to training is a modified version of the VGG16, specifically at the fully connected layer. Training is initiated for the weight adjustment of the initial convolution layer. Evaluative measures were undertaken based on the metrics delineated in this study.

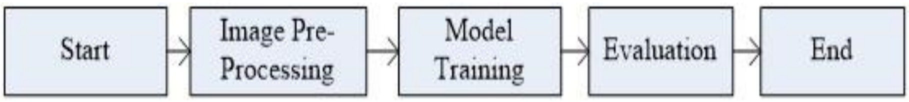


Figure 2. Research framework

2.3 Proposed Method

The diverse array of NTT ikat fabrics challenges users in discerning specific motifs and their respective regional origins. Such differentiation within multi-class classification represents a substantial challenge. To facilitate the recognition of ikat fabric motifs, a model underpinned by machine learning was developed. A comprehensive review of relevant literature reveals that the Convolutional Neural Network (CNN) method outperforms the handcrafted method in image retrieval as a feature extractor [12]. The architecture of a CNN encompasses convolution layers, pooling layers, and fully connected layers.
The VGG16 model was chosen for this research as the foundational CNN model. The VGG16 architecture evolved from the AlexNet framework, emphasizing the feature extraction process within the convolution layer. This design enables the capture of diverse image representations suitable for classification. The VGG16 model has 13 convolution layers complemented by three fully connected layers [3]. The VGG16 architecture is a great model with deeper layers and small convolution filter sizes for large datasets. The fundamental architecture of VGG16 is illustrated in Figure 3.
Confronting limited datasets poses significant challenges for deep learning models. Transfer learning emerges as a pivotal strategy to address such dataset constraints. This technique capitalizes on models that have been previously trained, adapting them for the classification of novel datasets. The VGG16 model, recognized as state-of-the-art, has been primed on expansive datasets, notably ImageNet. Leveraging such an adept model can alleviate computational demands, primarily

because it circumvents the need for training from scratch, focusing instead on adjustments to the model's terminal layer. Nevertheless, in the context of this study, modifications were instituted to align with the dataset's unique characteristics and to enhance overall model efficacy. The modified architecture of the VGG16 model, tailored for this study, is illustrated in Figure 4. Such modifications were implemented to better align with image characteristics and to enhance recognition accuracy.

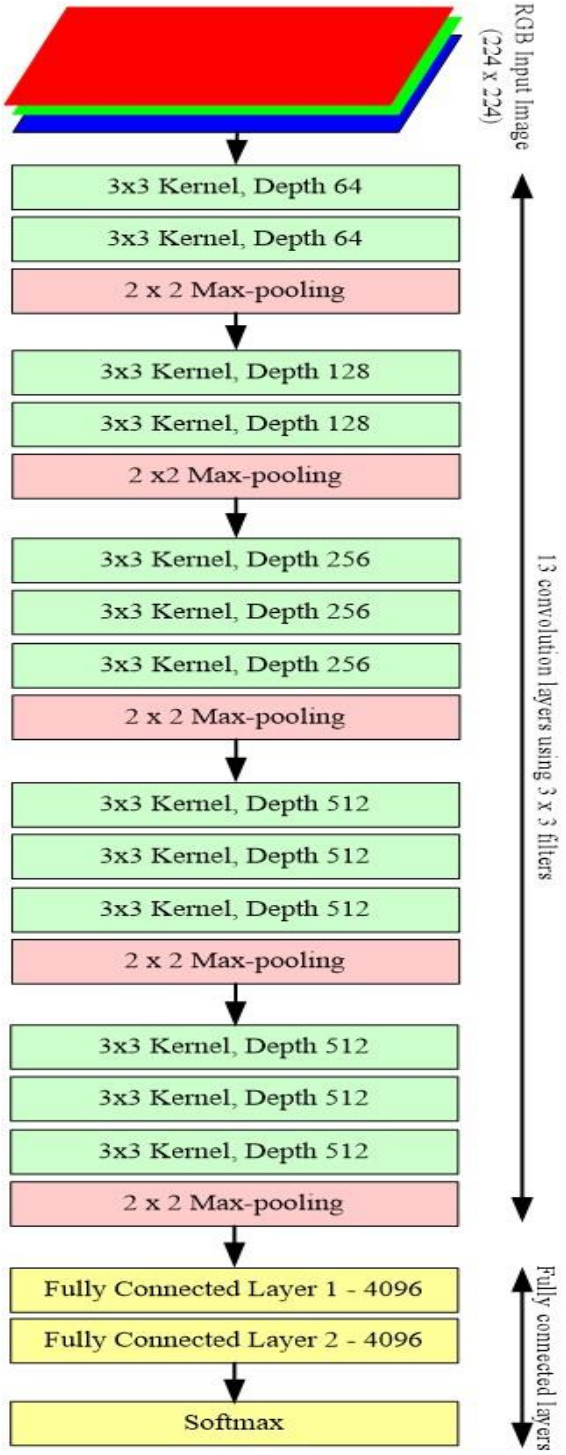


Figure 3. Baseline VGG16 model

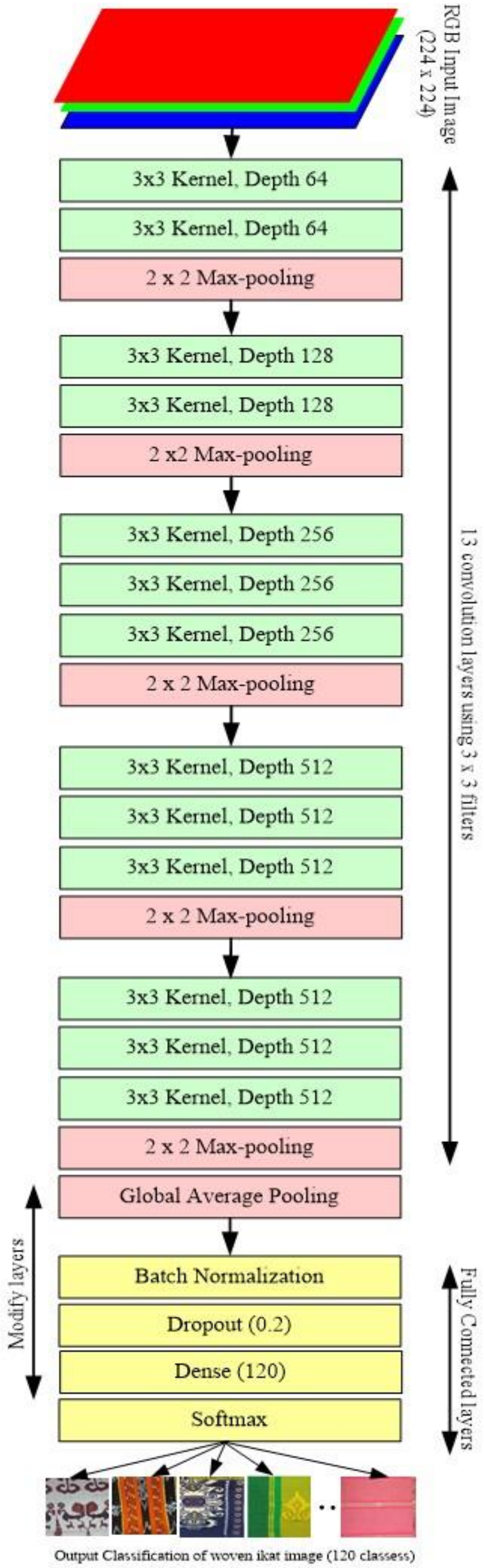


Figure 4. Modification of the VGG16 model for the classification of woven ikat fabric patterns.

1. Convolution and Max-pooling Function

Illustration of the convolution process between the input image and the filter in Figure 5 and Equation 1.

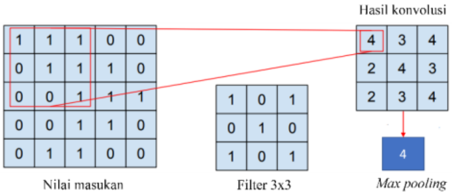


Figure 5. Convolution and *Max-pooling* processes [13].

$$g(x,y)=f(x,y) \times h(m,n) \quad 1$$

where $h(m,n)$ is the filter, $g(x,y)$ is the convolution image, and $f(x,y)$ is the original image.

2. Activation Functions

This research uses a non-linear activation function, namely Rectified Linear Unit (ReLU) [14] in each convolution layer. The ReLU activation equation is as follows:

$$R(x) = max\ (0, x) \quad 2$$

where x = input value. If the value of $x \leq 0$, then x=0 and the value of $x \geq 0$, then the value of $x=x$ In the output layer, softmax activation is used. The output value of the softmax activation function is between 0 and 1.

$$S(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}} \quad 3$$

where x= input value, n= number of data.

3. Loss Function

The loss function serves as a metric to evaluate the efficacy of the model's predictive capabilities regarding the target variable. In this study, categorical cross-entropy was employed due to the multi-class nature of the dataset.

$$H = -\sum_{x=1}^{N} P(x)\log\left(P(x)\right) \quad 4$$

with H = entropi, x = input data, N = number of data, and P = probability.

4. Fully Connected Layer

A fully connected layer is a layer that is used to carry out transformations on data dimensions so that they can be classified linearly. Before image features are entered into the FC layer, Global Average Pooling (GAP) is carried out to reduce overfitting due to limited training data. In the FC layer, Batch Normalization (BN) and Dropout are added to handle the overfitting problem caused by limited training data. Batch normalization is a technique in deep learning used to improve the speed and stability of model training. Dropout aims to deactivate some neurons that are not needed. In this study, the fully connected output was set to 120 according to the TenunIkatNet dataset. The baseline model adds GAP before the extracted features are entered into the FC layer.

Meanwhile, the proposed model at the FC layer adds GAP, BN, and dropout to reduce overfitting. The proposed model will be trained on 13 convolution layers. This process aims to adjust the weights and biases in the network from the initial convolution layer. Three layers of Global Average Pooling (GAP), Batch Bormalization (BN), and Dropout are incorporated to mitigate the risk of overfitting, ensuring the pretrained model adeptly represents and learns from novel data. In contrast, the baseline model undergoes the transfer learning process without modifying the weights and biases within the convolution layer. The training scenarios for the baseline model and the proposed model are illustrated in Figure 6.

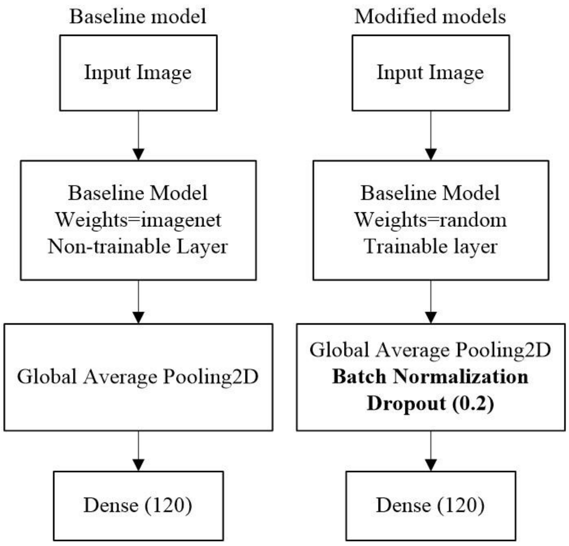


Figure 6. Transfer learning process of VGG16 and proposed models.

2.4 Performance Evaluation

Classification operates as a supervised learning procedure, relying on training sets derived from historical data. Key performance metrics in classification tasks encompass precision, recall, accuracy, and the F1-score [15]. For a comprehensive evaluation, it is instructive to juxtapose the model's classification outcomes against the actual classifications facilitated by the confusion matrix. The confusion matrix is a tabular representation elucidating the performance of a classification model on a test dataset for which valid values are established. As depicted in Figure 7, the confusion matrix encapsulates four distinct combinations of predicted and actual values. True positive (TP) represents instances where positive data is accurately predicted, while True Negative (TN) denotes correctly predicted negative data. Conversely, False Positive (FP) corresponds to instances where negative data is misclassified as positive, and False Negative (FN) signifies positive data erroneously predicted as negative [16].

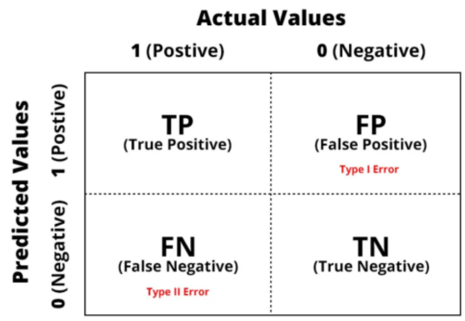


Figure 7. Confusion matrix.

Precision, as delineated in Equation 5, quantifies the proportion of correct positive predictions out of all positive predictions made.

$$Precision = \left(\frac{TP}{TP+FP}\right) x100\% \qquad 5$$

ecall, often termed sensitivity, provides insight into the model's efficacy in retrieving relevant instances. It is defined as the fraction of true positives over the sum of true positives and false negatives. This metric can be ascertained using Equation 6.

$$Recall = \left(\frac{TP}{TP+FN}\right) x100\% \qquad 6$$

accuracy serves as an indicator of the model's capability to classify instances correctly. Essentially, it measures the degree of congruence between predicted and actual values. The formula to compute accuracy is presented below:

$$Accuracy = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) x100\% \qquad 7$$

The F1-score is a metric used to compute the harmonic mean of precision and recall. An F1score approaching 1 signifies a balanced precision and recall.

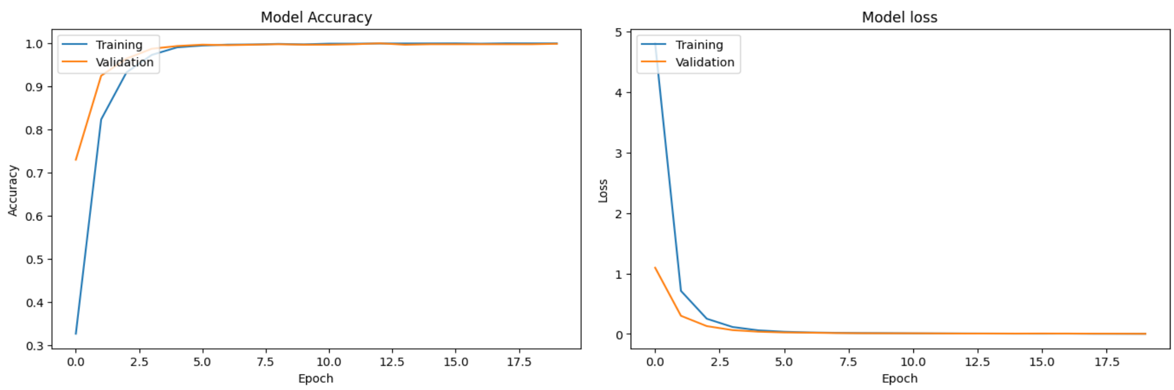
$$F1 = \left(\frac{TP}{TP+{}^{1}/_{2}(FP+FN)}\right) x100\% \qquad 8$$

3. RESULTS AND DISCUSSION

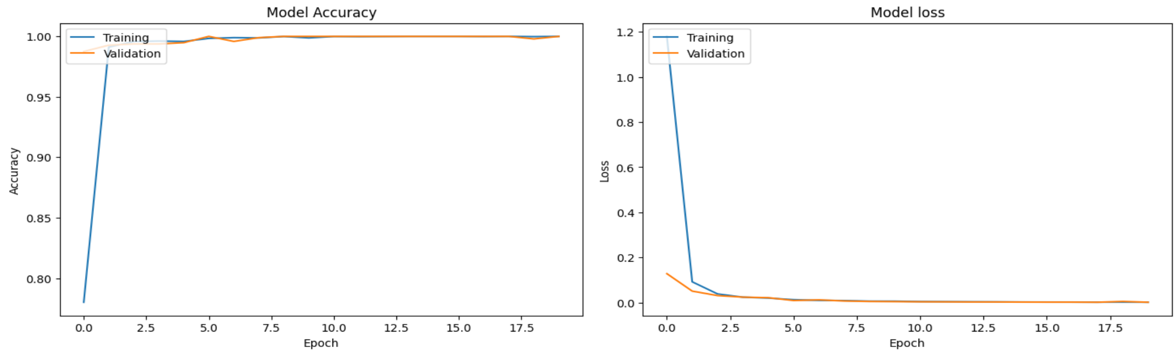
Research on the image classification of NTT ikat fabrics was conducted utilizing the Google Collaboratory platform. The hardware specifications encompassed an Nvidia T4 GPU with 16 GB GPU memory, a storage capacity of 166 GB, and 12 GB RAM. Additionally, computations were executed on a personal computer with an i5 10400F processor (3.0 GHz), 16 GB RAM, and a 250 GB storage capacity. For the implementation of the image classification model for ikat fabrics, the Python 3 programming environment was employed. Pertinent hyperparameters adopted in this study include a batch size of 64, a learning rate 0.001, and 20 epochs. The research leveraged the Adam optimizer to update network weights iteratively based on the defined loss function. The choice of these hyperparameters was informed by extant research demonstrating their efficacy[17], [13].

3.1 Experimental Results

The empirical findings indicate proficient recognition and classification capabilities for the VGG16 baseline model and its modified counterpart when handling ikat fabric images. Evaluating the training and validation accuracies, both models exhibit commendable performance. Initial epochs for both models signal to overfit, with convergence trends directing toward values of 1 and 0 for accuracy and loss metrics, respectively. Notably, the proposed model manifests heightened overfitting tendencies relative to the baseline model. Graphical in Figure 8 representations reveal persistent overfitting up to the 20th epoch. The training and validation accuracy metrics for the modified model trail those of the baseline model. This disparity can be attributed to the modified model's training phase, which emphasizes weight adjustments tailored to the new dataset, while the baseline model has been pre-trained on a more expansive dataset, specifically "ImageNet.



(a)



(b)

Figure 8. Graph of training and validation results for accuracy and loss,
(a) Baseline model, b) Proposed model.

The proposed model's architecture facilitates learning from novel datasets, enabling weight adjustments commencing from the primary convolution layer. The efficacy of the training phase intrinsically affects subsequent testing with the test dataset. The test outcomes underscore negligible disparities in accuracy metrics between the training and validation phases for both models. The proposed model showcases robus t performance, demonstrating adept generalization capabilities on the TenunIkatNet dataset, notwithstanding its prior training on a disparate dataset. Within the research context, regularization techniques such as batch normalization and dropout have proven efficacious in addressing overfitting concerns and have subsequently influenced model performance. Table 1 presents the accuracy and loss metrics for the training and validation phases of the two models under consideration.

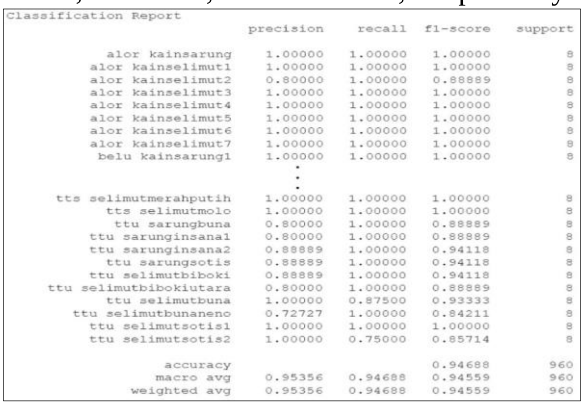
Table 1. Comparative training results of the baseline and proposed models.

Model	***Loss***	***Training Accuracy (%)***	***Val. Loss***	***Val. Accuracy (%)***
Baseline model	0.003	99.78	0.003	99.89
Proposed model	0.071	98.26	0.353	98.54

The classification test for the testing data encompassed 960 images of ikat woven fabric, distinct from those utilized in the training phase. According to the established evaluation metrics, the proposed model surpasses the performance of the baseline model. Figure 9 displays the classification report based on the metrics used in this research. The proposed model yields values for accuracy, precision, recall, and F1-score of 98.542%, 98.729%, 98.542%, and 98.531%, respectively.

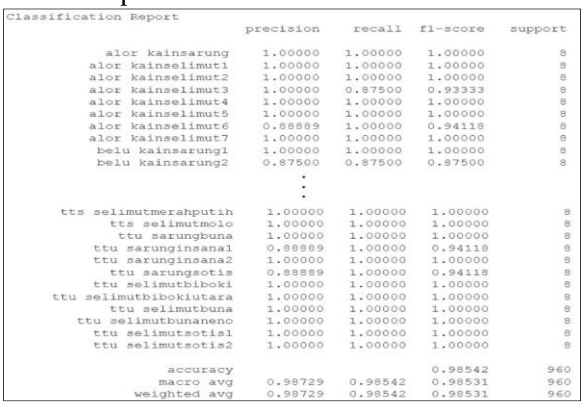
Conversely, the baseline model demonstrates an advantage when evaluating the number of trained parameters and the model's footprint. Specifically, the baseline model's size is notably more compact than the proposed model's.

A comparative assessment encompassing four key metrics, model size, and the number of parameters is presented in Table 2. These supplementary metrics are derived from the underlying architecture of the respective models.


Classification Report

	precision	recall	f1-score	support
alor kainsarung	1.00000	1.00000	1.00000	8
alor kainselimut1	1.00000	1.00000	1.00000	8
alor kainselimut2	0.80000	1.00000	0.88889	8
alor kainselimut3	1.00000	1.00000	1.00000	8
alor kainselimut4	1.00000	1.00000	1.00000	8
alor kainselimut5	1.00000	1.00000	1.00000	8
alor kainselimut6	1.00000	1.00000	1.00000	8
alor kainselimut7	1.00000	1.00000	1.00000	8
belu kainsarung1	1.00000	1.00000	1.00000	8
	⋮			
tts selimutmerahputih	1.00000	1.00000	1.00000	8
tts selimutmolo	1.00000	1.00000	1.00000	8
ttu sarungbuna	0.80000	1.00000	0.88889	8
ttu sarunginsana1	0.80000	1.00000	0.88889	8
ttu sarunginsana2	0.88889	1.00000	0.94118	8
ttu sarungsotis	0.88889	1.00000	0.94118	8
ttu selimutbiboki	0.88889	1.00000	0.94118	8
ttu selimutbibokiutara	0.80000	1.00000	0.88889	8
ttu selimutbuna	1.00000	0.87500	0.93333	8
ttu selimutbunaneno	0.72727	1.00000	0.84211	8
ttu selimutsotis1	1.00000	1.00000	1.00000	8
ttu selimutsotis2	1.00000	0.75000	0.85714	8
accuracy			0.94688	960
macro avg	0.95356	0.94688	0.94559	960
weighted avg	0.95356	0.94688	0.94559	960

(a)


Classification Report

	precision	recall	f1-score	support
alor kainsarung	1.00000	1.00000	1.00000	8
alor kainselimut1	1.00000	1.00000	1.00000	8
alor kainselimut2	1.00000	1.00000	1.00000	8
alor kainselimut3	1.00000	0.87500	0.93333	8
alor kainselimut4	1.00000	1.00000	1.00000	8
alor kainselimut5	1.00000	1.00000	1.00000	8
alor kainselimut6	0.88889	1.00000	0.94118	8
alor kainselimut7	1.00000	1.00000	1.00000	8
belu kainsarung1	1.00000	1.00000	1.00000	8
belu kainsarung2	0.87500	0.87500	0.87500	8
	⋮			
tts selimutmerahputih	1.00000	1.00000	1.00000	8
tts selimutmolo	1.00000	1.00000	1.00000	8
ttu sarungbuna	1.00000	1.00000	1.00000	8
ttu sarunginsana1	0.88889	1.00000	0.94118	8
ttu sarunginsana2	1.00000	1.00000	1.00000	8
ttu sarungsotis	0.88889	1.00000	0.94118	8
ttu selimutbiboki	1.00000	1.00000	1.00000	8
ttu selimutbibokiutara	1.00000	1.00000	1.00000	8
ttu selimutbuna	1.00000	1.00000	1.00000	8
ttu selimutbunaneno	1.00000	1.00000	1.00000	8
ttu selimutsotis1	1.00000	1.00000	1.00000	8
ttu selimutsotis2	1.00000	1.00000	1.00000	8
accuracy			0.98542	960
macro avg	0.98729	0.98542	0.98531	960
weighted avg	0.98729	0.98542	0.98531	960

(b)

Figure 9. Results of image classification of woven ikat fabrics
(a) baseline model, b) proposed model

Table 2. Comparison results of the model testing for both classification models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Number of Parameters	Model size (MB)
Baseline model (VGG16)	94.688	95.356	94.688	94.559	14,776,248	56.9
Proposed model	98.542	98.729	98.542	98.531	14,777,272	169.2

The architecture of the resultant model, illustrating the sizes of input and output images, is delineated in Figure 10. The computation for the number of parameters is derived from the product of the filter size and the input image size, augmented by the bias, and subsequently multiplied by the output channel. Within the VGG16 baseline model, the parameter count stands at 14,776,248, of which 61,560 are associated with the fully connected layers undergoing training. In contrast, the proposed model trains 14,777,272 parameters, given that its training scope extends from the initial convolution layer to the FC layer. Excluded from the training process are 1,024 parameters, specifically within the global average pooling and dropout layers. A reduction in untrained parameters can effectively alleviate computational demands. Additionally, the quantity of trained parameters intrinsically influences the model's footprint. The parameter count is a function of filter size, filter count, and input and output dimensions. A larger pool of untrained parameters can correspondingly diminish the model's size. Optimal performance is characterized by a minimal parameter count paired with a compact model size, facilitating its deployment in real-time applications.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 global_average_pooling2d (G  (None, 512)              0
 lobalAveragePooling2D)

 dense (Dense)               (None, 120)               61560

=================================================================
Total params: 14,776,248
Trainable params: 61,560
Non-trainable params: 14,714,688
```

(a)

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 global_average_pooling2d (G  (None, 512)              0
 lobalAveragePooling2D)

 batch_normalization (BatchN  (None, 512)              2048
 ormalization)

 dropout (Dropout)           (None, 512)               0

 dense (Dense)               (None, 120)               61560

=================================================================
Total params: 14,778,296
Trainable params: 14,777,272
Non-trainable params: 1,024
```

(b)

Figure 10. Architecture of the model and the quantity of parameters engaged in training (a) Baseline model, (b) Proposed model.

3.2 Discussion

This study presents the training performance outcomes of the woven ikat fabric image classification model, utilizing both the VGG16 baseline model and the proposed modification. The evaluation criteria focus on the model's accuracy and propensity for overfitting. Accuracy is defined as the proportion of correct predictions from the test data, whereas overfitting is assessed by comparing the model's training accuracy to its validation accuracy.

The empirical findings suggest that the modified model offers superior results to the baseline model. The proposed model demonstrates excellence in predicting test data against training data categories, with only a few classifications deviating from their valid category. Notably, the characteristics of NTT ikat fabric images diverge from those of the ImageNet dataset, which served as the foundational training set for the baseline model. Dominated by geometric patterns, such as lines, edges, and dots, the inherent features of ikat fabrics emerge predominantly in convolution layers. Consequently, the proposed model, which undergoes training starting from the initial convolution layer, shows enhanced accuracy in classifying ikat fabric images. Despite the constrained size of the TenunIkatNet dataset, regulatory methods can mitigate the risk of pronounced overfitting. The results underscore the efficacy of implementing dropout and batch normalization within the fully connected layer in curtailing overfitting issues.

In the context of limited datasets, one could also consider designing a more streamlined CNN architecture tailored to the distinct visual characteristics of NTT ikat fabrics. Given the rich foundational features in the images of ikat woven

fabrics, a reduced layer depth might be more appropriate. The dimensions and quantity of filters can have a direct impact on the performance of the model. Introducing batch normalization across layers can further minimize overfitting. Moreover, incorporating global average pooling at the culmination of the convolution process, combined with dropout layers, can combat overfitting and enhance accuracy[17].
For future studies, expanding the dataset will offer a more rigorous assessment of the proposed model's performance. Additionally, testing the model against diverse dataset variations, including alterations in lighting, geometry, and image resolution stemming from varied recording instruments, will provide a comprehensive evaluation.

4. CONCLUSION

Ikat woven fabric is renowned for its intricate variety of motifs, posing challenges for recognition. The cultural significance of the ikat fabric underscores the imperative for its preservation. This study employs the TenunIkatNet dataset, comprising 120 distinct classes and encompassing a total of 4,800 images. A prevalent technique for identifying these motifs involves classification, specifically delineating based on motif type and geographical provenance. In this study, the Convolutional Neural Network (CNN) method is adopted for feature extraction, with a particular emphasis on the VGG16 model, recognized for its state-of-the-art capabilities. Given the model's pre-existing proficiency owing to its training on extensive datasets, the transfer learning strategy is employed for classification. This research juxtaposes the performance of the standard VGG16 model with a modified variant that incorporates alterations in the fully connected layer. For the proposed model, weight adjustments are initiated from the very first convolution layer, a strategic move aimed at tailoring the model to the nuances of the TenunIkatNet dataset. The rationale behind this transfer learning approach is the pursuit of optimal model performance. Empirical findings indicate that adaptations in the fully connected layer, coupled with weight training initiated from the primary convolution layer, yield superior results relative to the baseline model. Incorporating elements like Global Average Pooling (GAP), Batch Normalization (BN), and Dropout mitigates overfitting and bolsters model performance per evaluation metrics. Analyzing the results through established evaluation metrics reveals the proposed model's supremacy over the baseline, registering precision, recall, accuracy, and F1-score values of 98.73%, 98.54%, 98.54%, and 98.53%, respectively. Notably, in terms of trained parameter count and overall size, the baseline model is more compact than its proposed counterpart.

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