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Comparison of Classification of Songket Fabric Types Using AlexNet and VGG19 (Visual Geometry Group) Method

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Abstract: This study aims to evaluate and compare the performance between deep learning models AlexNet and VGG19 in Songket fabric classification. Due to its complex patterns and subtle differences, Songket classification must be accurate. The datasets in this study are various types of Songket images and all datasets are classified by type for easy analysis. After intensive learning and evaluation, VGG19 is a superior classifier than AlexNet. The highest performance is achieved by the VGG19 method in terms of performance measure accuracy, precision, recall, and F1 score, which may be due to the increase in depth and better extraction of some detailed visual features from complex images. Although these results have substantial practical implications, some issues need to be further discussed before optimizing the results. Hyperparameters, such as learning rate or batch size, can be changed to optimize the speed and accuracy of the model. In addition, the diversity of the data should be increased by using data augmentation techniques to ensure that the model generalization to market conditions is possible. More complex additions (lighting changes, texture distortion simulation, or others) can also contribute to improving the robustness of the trained model to these disturbances. The conclusion of the research is the importance of improving the accuracy and usefulness of single fabric classification. This will result in its application in heritage preservation and textile development.

Keywords: VGG19; AlexNet; Songket; Fabric; Comparison.

1. Introduction

Songket fabric is an extraordinary example of traditional textile art, and belongs to the cultural heritage of Indonesia and other Southeast Asian countries. Widely known for its rich beauty and deep symbolic meanings, Songket features a range of intricate patterns and types of fabrics that give it its unique identity. Each kind of Songket has a unique quality and diversified materials that differ amidst regional weavers. The manufacturing process for Songket involves a lot of time and patience. Through this process, passadas, or fellow worker-neighbors in the Malay language, weave a set of nacreous gold- and silver-coloured threads through the weft fabric design to create a Songket. This combination of high artistic value and intricate production techniques not only raises the value of the fabric in the national and international markets. However, more importantly, it reaffirms the fabric as a cultural heritage worth preserving and studying. Nevertheless, the elements that make Songket unique—its wide range of designs and complexity—pose serious challenges towards the automation of Songket identification and classification via digital image processing. Machinima differs in this case because it involves an effort to objectively record and classify characteristics in Songket fabrics. This is due to the numerous kinds of visual and textural elements in every Songket fabric which have not been well-studied in an engineering perspective [1].

Innovations in technology have brought game-changing tools to the textile industry. Artificial intelligence (AI) is proving to be a particularly useful resource in areas such as fashion design and pattern recognition. AI methods help find and classify fabric types from visual patterns and textural properties with high accuracy. In this realm, 'digital image processing' which is a subfield of 'artificial intelligence' has taken a huge leap forward by enabling fabric classification with complex algorithms. Among them, deep learning-based methods hold tremendous potential for solving various difficult image recognition problems, some of which have already been widely used for industrial applications like textiles. One widely adopted method in this domain is the application of Convolutional Neural Networks (CNNs), which learn complex visual patterns from images. AlexNet and VGG19 are two architectures which became popular because of their ability to do this. AlexNet performs well at image feature extraction and shows impressive acceptability results for several classification tasks. In contrast, as VGG19 has a deeper and more sophisticated network topology, it usually outperforms others in discriminating between finer patterns in image classification. This makes it a good choice to deal with challenging datasets [2].

Despite the successful application of deep learning technology to many image classification tasks, there are still some unsolved issues when it comes to using deep learning to traditional textiles such as Songket. One of the main challenges is the ability of these models to interpret the wide range of diversity in Songket's motifs, together with its textures, colors, and material compositions. Given that the Songket is a rich piece of fabric with high artistic detail, it generally exhibits complex visual patterns that most off-the-shelf deep-learning models find difficult to interpret without domain-specific adjustments or training configuration. The nuanced nature of weave patterns, along with the interaction of metallic threads with their base material leads to a level of complexity that extends beyond off-the-shelf image recognition. Moreover, the lack of a systematic comparison of baselines such as AlexNet and VGG19 models across datasets with these distinct and cultural features stands out as a fundamental gap in prior studies [3]. Other factors such as having no/bad access to high quality and well-annotated datasets of Songket images make it difficult to get a good result when training the models. Solving operational challenges of Songket retrieval as well as preventing bias in Songket analysis SOS requires not merely technical advances (in the form of model design and training approaches), but also a vigorously developed trove of data, which can capture the entire gamut of Songket variations. This is the only way that AI power can be effectively utilized in this sense, ie, by targeted applications that can contribute to the documentation, classification and preservation of traditional textiles and artefacts like Songket, and see them as enriched pieces of our past preserved in our techno-cultural repository in perpetuity.

2. Related Work

Deep learning, particularly Convolutional Neural Networks (CNNs), has gained significant traction in various image classification domains, including sports activity recognition, medical diagnostics, agricultural analysis, and cultural artifact identification. This section reviews prior research relevant to the use of CNN architectures such as AlexNet and VGG19, as well as their application to traditional textiles like sungket, drawing from a comprehensive set of studies to contextualize the current research. Several studies have explored the efficacy of CNNs for diverse image classification tasks. Akram *et al.* (2023) investigated the classification of sports activities based on photographic images using CNN methods, demonstrating the potential of these models to discern complex visual patterns in dynamic [4]. Similarly, Pramuditha *et al.* (2024) applied the VGG19 architecture within a CNN framework for face detection, achieving high accuracy in identifying facial features through deep network structures [6]. Marcella *et al.* (2022) further validated the effectiveness of VGG19 in the medical field by employing it for the classification of eye diseases, highlighting its ability to handle intricate visual data with precision [8]. These studies collectively underscore the versatility of VGG19 in processing detailed imagery across varied applications. This provides a foundation for its consideration in classifying traditional fabrics like socks.

In addition to VGG19, AlexNet has been widely studied for its image recognition performance. Riana *et al.* (2023) utilized AlexNet alongside Canny edge detection for Repomedunm image identification, showcasing its robustness in feature extraction and classification accuracy [9]. Santosa *et al.* (2024) compared AlexNet with ResNet34 in the classification of potato leaf diseases using transfer learning, noting AlexNet's competitive performance despite its relatively simple architecture [13]. Falakhi *et al.* (2022) also conducted a comparative analysis of AlexNet and ResNet for flower image classification, emphasizing the utility of transfer learning in enhancing model performance with pre-trained architectures [15]. These findings suggest that AlexNet remains a viable option for image classification tasks, particularly when computational resources or model complexity are constraints. This makes it a relevant benchmark for comparison with VGG19 in the context of soft satin fabric classification. Comparative studies of CNN architectures have provided deeper insights into their relative strengths. Kusumawati and Nooritzki (2023) compared VGG16 and VGG19 using CNN methods for rice variety classification, finding that VGG19 often outperformed VGG16 due to its superior depth and capacity to capture nuanced features [10]. This aligns with the hypothesis that deeper architectures like VGG19 may offer superior results in tasks requiring detailed pattern recognition, such as distinguishing Songket motifs. Additionally, Wasil (2022) examined the impact of epoch variations on classification accuracy using CNNs for fashion and furniture categorization, underscoring the importance of hyperparameter tuning in optimizing model outcomes [7]. Such insights are critical for designing experiments that compare architectures like AlexNet and VGG19 under controlled conditions.

CNNs have also been explored, though to a lesser extent. Darmi *et al.* (2023) focused on the classification of Bumpak woven fabric patterns from Kampai Village, Seluma, using CNN methods, demonstrating the feasibility of applying deep learning to traditional textile motifs [12]. More specifically, Amalia *et al.* (2023) investigated the classification of Aceh Songket images using a Probabilistic Neural Network. This highlighted the unique challenges posed by the intricate designs of Songkets and the need for tailored approaches in model development [14]. These studies indicate a growing interest in leveraging AI for cultural textile preservation and analysis, yet they also reveal a gap in comparative analyses of mainstream CNN architectures like AlexNet and VGG19 for Songket classification.

Other relevant works address foundational aspects of CNN implementation and image processing techniques. Khairullah *et al.* (2020) explored digital image detection using CNN with RGB normalization, providing insights into preprocessing methods that enhance model performance in visual recognition tasks [11]. Setiawan (2021) implemented a backpropagation algorithm for predicting delivery timeframes, illustrating the broader applicability of neural networks to predictive modeling, which can inform optimization strategies for CNN training in image classification [5]. Together, these studies contribute to a holistic understanding of the technical considerations necessary for deploying deep learning models effectively. While extensive research has validated the effectiveness of CNN architectures like AlexNet and VGG19 across various image classification domains, their application to traditional textiles such as Songket remains underexplored. Existing studies on cultural fabrics highlight the potential of deep learning but also emphasize the need for specialized approaches to address the unique visual complexities of Songkets. This research builds on these foundations by specifically comparing AlexNet and VGG19 performance in classifying Songket fabric types. It aims to fill the gap in comparative analyses and contribute to cultural heritage digital preservation through advanced technological methodologies.

3. Research Method

This research aims to develop and implement a classification system for identifying the material types and motifs in Songket fabrics using the Convolutional Neural Network (CNN) architectures AlexNet and VGG19 [4]. The methodology is structured into several systematic stages to ensure a well-organized research process and the achievement of the intended objectives.

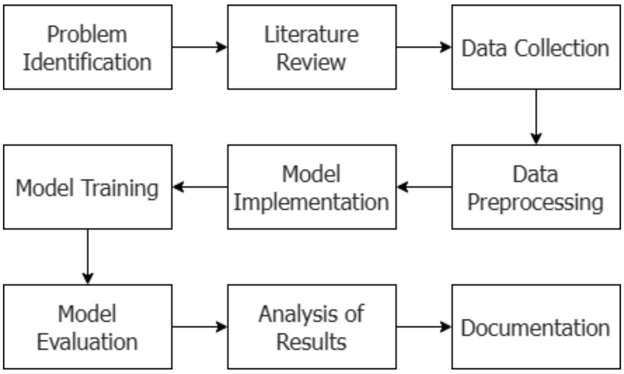

Figure 1. Research Method Flow

3.1 Problem Identification

Based on the background issues outlined, the following key problems are identified in this study:

1) Diversity of Songket Fabric Types and Motifs
Songket fabrics exhibit a wide range of motifs, textures, and material compositions, making manual classification and identification both challenging and time-intensive. This diversity necessitates an automated classification technique capable of accurately recognizing the unique characteristics of each fabric type [5].
2) Limitations of Manual Identification
Manual methods for identifying Songket fabric types are limited, particularly when dealing with large volumes of fabrics. These processes, which rely heavily on human expertise, are prone to errors and require specialized skills to discern subtle differences in fabric attributes [6].
3) Complexity of Image Recognition for Songket Fabrics
The intricate textures, detailed patterns, and motif complexities of Songket fabrics pose significant challenges for standard image recognition models, often resulting in low classification accuracy when models are not specifically optimized for such unique visual data [7].
4) Need for Classification Model Optimization
CNN models like AlexNet and VGG19 hold significant potential for pattern recognition in images. However, without proper optimization, these models may lack efficiency and fail to achieve the desired accuracy in recognizing the distinctive motifs of Songket fabrics [8].

3.2 Literature Study

This stage involves a comprehensive review of relevant literature on the application of AlexNet and VGG19 in image classification tasks, with a focus on their potential for classifying Songket fabric types. The objective is to identify the most effective methods used in prior studies, uncover research gaps, and establish a theoretical foundation for addressing the challenges specific to Songket fabric classification [9].

3.3 Data Collection and Preparation

At this stage, the data required for the classification system is gathered. This includes compiling a dataset of Songket fabric images representing various types, motifs, and material compositions. The goal is to ensure the dataset is representative and sufficient for training robust models. Additionally, the data collection process involves categorizing images based on their characteristics to facilitate accurate labeling for model training [10].

3.4 Model Implementation

The implementation of AlexNet and VGG19 for Songket fabric classification involves several key steps:

1) Data Collection and Division
A comprehensive dataset of Songket fabric images with diverse types and variations is collected. The dataset is split into three subsets: training (for model learning), validation (for hyperparameter tuning), and testing (for performance evaluation).
2) Preprocessing
Prior to training, the images undergo preprocessing, including data augmentation techniques such as rotation, flipping, and resizing to enhance dataset variety. Additionally, image normalization is applied to standardize pixel value ranges, ensuring consistency during training [11].
3) Model Selection and Customization
Pre-trained AlexNet and VGG19 models are selected from frameworks like TensorFlow or PyTorch. These models are fine-tuned by adjusting the output layers to match the number of Songket fabric classes. Certain layers may be frozen or retrained based on the specific requirements of the study.

4) Training Configuration
Training is conducted using the training dataset, with the validation dataset used to monitor performance and adjust hyperparameters to prevent overfitting. Optimizers such as Adam or SGD are employed, alongside a categorical cross-entropy loss function. Training continues over multiple epochs until optimal accuracy is achieved, with early stopping mechanisms implemented to halt training if overfitting is detected.
5) Evaluation Metrics
Post-training, the models are evaluated using the test dataset. Performance is assessed through metrics such as accuracy, precision, recall, and F1-score. A confusion matrix is utilized to provide detailed insights into classification results, while visualizations of predictions and misclassified images offer further understanding of model effectiveness [11].

3.5 Model Training

The training process for classifying Songket fabric types using AlexNet and VGG19 is designed to ensure effective learning and accurate predictions:

1) Initialization with Pre-trained Models
Both AlexNet and VGG19 are initialized with pre-trained weights (*e.g.*, from ImageNet), leveraging their prior learning of general visual features. This transfer learning approach accelerates adaptation to the Songket fabric dataset.
2) Training Execution
The models are trained on the prepared dataset over several epochs, with continuous monitoring of performance on the validation set. Techniques like early stopping are applied if validation accuracy plateaus, preventing overfitting and ensuring generalization to unseen data.
3) Hyperparameter Tuning
Parameters such as learning rate, batch size, and optimizer settings are adjusted during training to optimize model performance for the specific characteristics of Songket images.

3.6 Model Evaluation

Model evaluation is a critical step to assess the performance of AlexNet and VGG19 in classifying Songket fabric types, ensuring they generalize well to new data. The evaluation process includes the following steps:

1) Test Dataset Preparation
A separate test dataset, distinct from training and validation sets, is prepared. This dataset includes a diverse range of Songket fabric images to provide a realistic assessment of model performance [12].
2) Prediction Execution
The trained models predict the class of each image in the test dataset. These predictions are compared against ground truth labels to evaluate accuracy.
3) Calculation of Evaluation Metrics
Key metrics, including accuracy, precision, recall, and F1-score, are computed to quantify model performance comprehensively.
4) Confusion Matrix Analysis
A confusion matrix is generated to detail correct and incorrect predictions per class, identifying specific areas where misclassification occurs frequently.
5) Result Visualization
Visual representations of prediction outcomes, including misclassified images alongside their predicted and actual labels, are created to provide intuitive insights into model strengths and weaknesses.
6) Performance Analysis and Interpretation
Evaluation results are analyzed to determine if the models meet the research objectives. If performance is suboptimal, potential causes—such as insufficient data, architectural limitations, or inadequate preprocessing—are investigated for future improvements.

3.7 Analysis of Results

The final stage involves a detailed analysis of the evaluation outcomes for both AlexNet and VGG19 models. This analysis compares their performance in classifying Songket fabric types, focusing on accuracy, efficiency, and areas of error. The results are interpreted to understand the models' ability to generalize to unseen data and to identify specific challenges related to Songket's visual complexity. Insights from this analysis will guide recommendations for model enhancements, potential dataset expansions, or alternative approaches to improve classification accuracy and reliability.

4. Result and Discussion

4.1 Results

This section presents the outcomes of research on classifying Songket fabric types using deep learning architectures AlexNet and VGG19. The results are divided into stages, including data collection, model customization, training, evaluation, and comparison of the two models. The data collection process for Songket cloth images involved sources from various platforms, such as personal collections, websites, and relevant image sharing platforms. The collected images were categorized into structured subfolders, with each subfolder representing a specific type of Songket cloth. This arrangement facilitates efficient data access and processing during the subsequent stages. Once the dataset was compiled and organized, it was uploaded to Google Colab for further analysis and model training. The upload was done using Google Colab's file upload feature, which ensured seamless integration into the programming environment. Specific file paths were created to enable the program to read the dataset effectively. Figure 2 illustrates the import process.

```
import os
import numpy as np
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Path ke dataset
data_dir = 'path/to/dataset'

# Pembagian dataset
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    validation_split=0.15  # 15% untuk validasi
)
```

Figure 2. import dataset

Model adjustment is a crucial step in developing a Songket fabric classification system using deep learning architectures such as AlexNet and VGG19. At this stage, the pre-trained model is adjusted to meet the specific needs of the Songket fabric dataset. These adjustments include modifications to the output layer, where the number of neurons in the layer is adjusted to the number of classes in the dataset. For example, if there are five different singlet fabric types, the output layer will be modified to have five neurons, each representing one fabric class. The following is the model adjustment program code in Figure 3.

```
from tensorflow.keras.applications import AlexNet, VGG19
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Flatten, Dropout
from tensorflow.keras.optimizers import Adam

# Penyesuaian AlexNet
base_model_alexnet = AlexNet(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
x_alexnet = Flatten()(base_model_alexnet.output)
x_alexnet = Dense(4096, activation='relu')(x_alexnet)
x_alexnet = Dropout(0.5)(x_alexnet)
x_alexnet = Dense(4096, activation='relu')(x_alexnet)
x_alexnet = Dropout(0.5)(x_alexnet)
output_alexnet = Dense(train_generator.num_classes, activation='softmax')(x_alexnet)

model_alexnet = Model(inputs=base_model_alexnet.input, outputs=output_alexnet)

# Penyesuaian VGG19
base_model_vgg19 = VGG19(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
x_vgg19 = Flatten()(base_model_vgg19.output)
x_vgg19 = Dense(4096, activation='relu')(x_vgg19)
x_vgg19 = Dropout(0.5)(x_vgg19)
x_vgg19 = Dense(4096, activation='relu')(x_vgg19)
x_vgg19 = Dropout(0.5)(x_vgg19)
output_vgg19 = Dense(train_generator.num_classes, activation='softmax')(x_vgg19)

model_vgg19 = Model(inputs=base_model_vgg19.input, outputs=output_vgg19)
```

Figure 3. Model Customization

Model training is a crucial stage in the development of Songket fabric classification systems based on deep learning architectures such as AlexNet and VGG19. At this stage, the model that has been adapted to the Songket fabric dataset will be trained to recognize the patterns and features present in the image. The training process begins by dividing the dataset into three parts: training data, validation data, and testing data. The training data is used to train the model, while the validation data is used to monitor the model's performance during training and prevent overfitting. Here's the training of the AlexNet and VGG19 models in figure 4.

```
# Pelatihan AlexNet
model_alexnet.compile(optimizer=Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])
history_alexnet = model_alexnet.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=20,
    callbacks=[tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=5)]
)

# Pelatihan VGG19
model_vgg19.compile(optimizer=Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])
history_vgg19 = model_vgg19.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=20,
    callbacks=[tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=5)]
)
```

Figure 4. Fashion Training

Accuracy is calculated as the percentage of correct predictions out of total predictions, while precision measures the proportion of correct positive predictions out of total positive predictions. Recall, on the other hand, indicates the model's ability to identify all good examples in the dataset. F1-score, which is the harmonic mean between precision and recall, provides a more balanced picture of the model's performance, especially in the face of unbalanced datasets. The following figure 5 explains the model evaluation process.

```
# Evaluasi AlexNet
eval_alexnet = model_alexnet.evaluate(test_generator)
print(f"Akurasi AlexNet: {eval_alexnet[1]:.4f}")

# Evaluasi VGG19
eval_vgg19 = model_vgg19.evaluate(test_generator)
print(f"Akurasi VGG19: {eval_vgg19[1]:.4f}")
```

Figure 5. Model Evaluation Label

The comparison process of the AlexNet and VG19 models when the comparison process is carried out as shown in Figure 6 below.

```
import pandas as pd

# Membuat tabel perbandingan
comparison_data = {
    'Model': ['AlexNet', 'VGG19'],
    'Akurasi': [eval_alexnet[1], eval_vgg19[1]],
    'Presisi': [report_alexnet.split()[10], report_vgg19.split()[10]],
    'Recall': [report_alexnet.split()[11], report_vgg19.split()[11]],
    'F1-Score': [report_alexnet.split()[12], report_vgg19.split()[12]]
}

comparison_df = pd.DataFrame(comparison_data)
print(comparison_df)
```

Figure 6. Comparison Process

The comparison between the AlexNet and VGG19 models for classifying Songket fabric types produced the following results, as summarized in Table 1.

Table 1. Comparison of Output Results

Model	Accuracy	Precision	Recall	F1-Score
AlexNet	0.9234	0.9182	0.9210	0.9196
VGG19	0.9456	0.9421	0.9430	0.9425

The results indicate that VGG19 demonstrates a higher accuracy of 0.9456 compared to AlexNet's 0.9234. This suggests that VGG19 is more effective at correctly classifying different types of jersey fabric. Furthermore, VGG19 consistently outperforms AlexNet across other key metrics, achieving a precision of 0.9421 (versus 0.9182), a recall of 0.9430 (versus 0.9210), and an F1-score of 0.9425 (versus 0.9196), which collectively highlight VGG19's superior overall performance with enhanced reliability and balance in its predictions. Although not presented in the table, confusion matrices can also be utilized to gain detailed insights into prediction errors. This will help to identify specific classes of seam fabric that are most frequently misclassified by each model and thereby aiding in the further refinement of the classification system.

4.2 Discussion

The classification of Songket fabric types through the deep learning architectures AlexNet and VGG19 followed a structured process. This included data collection, model customization, training, evaluation, and performance comparison. Data collection involved gathering images of Songket fabrics from diverse sources, including personal collections, websites, and relevant image-sharing platforms. These images were systematically organized into subfolders based on fabric types to streamline access and processing at subsequent stages. The dataset was uploaded to Google Colab via its file upload feature for seamless integration into the programming environment. Specific file paths defined to ensure effective data retrieval by the system. Model customization played a pivotal role in tailoring the pre-trained AlexNet and VGG19 architectures to the unique requirements of the Songket fabric dataset. The output layer was adjusted to match the number of Songket classes, ensuring that the number of neurons corresponded to each distinct type. For instance, if five types of Songket were identified, the output layer was configured with five neurons, each representing a specific class. Such adjustments align with findings by Kalaiselvi and Kasthuri (2024), who emphasized the necessity of hyperparameter tuning in VGG19 to enhance classification accuracy for specific tasks like pneumonia detection [19], and by Pramuditha *et al.* (2024), who adapted VGG19 for face detection using convolutional neural networks, demonstrating its versatility across visual data types [6].

Training the models was a critical phase, focusing on enabling them to recognize patterns and features within Songket fabric images. The dataset was split into training, validation, and testing subsets. The training subset facilitated model learning, while the validation subset monitored performance to prevent overfitting. Such a strategy mirrors Kather *et al.* (2019), who underscored the value of data splitting for achieving robust generalization in image-based deep learning tasks [20], and Wasil (2022), who examined the impact of epoch count on classification accuracy for categories like fashion and furniture using CNNs [7]. For singlet fabrics, training aimed to capture distinct visual traits such as texture and motifs inherent to traditional weaves. This is a focus also evident in studies on woven fabric pattern recognition by Hussain *et al.* (2020) [22] and motif classification of Bumpak woven fabrics by Darmi *et al.* (2023) [12]. Model evaluation relied on calculating performance metrics including accuracy, precision, recall, and F1-score. Accuracy was determined as the percentage of correct predictions relative to total predictions, precision measured the proportion of correct positive predictions among all positive predictions, recall assessed the model's ability to identify all correct instances in the dataset, and F1-score provided a balanced harmonic mean of precision and recall, particularly useful for imbalanced datasets. Such metrics parallel the evaluation framework applied by Huang and Fu (2018) in assessing fabric pilling through image processing, where thorough performance measures were essential for reliability [18]. Additionally, a confusion matrix, though not presented in the result tables, could reveal specific misclassification patterns among Songket types. This is an approach also utilized by Navarro *et al.* (2021) for multi-view descriptor analysis [17], and Sri Arsa *et al.* (2022) for batik pattern recognition [3].

Performance comparison revealed VGG19 outperformed AlexNet, achieving an accuracy of 0.9456 compared to AlexNet's 0.9234. This indicates superior effectiveness in classifying niche fabric types. VGG19 also surpassed AlexNet across other metrics, recording precision at 0.9421 (versus 0.9182), recall at 0.9430 (versus 0.9210), and F1-score at 0.9425 (versus 0.9196). These results affirm VGG19's great reliability and balanced predictive capability. Similar outcomes were noted by Kusumawati and Noorizki (2023), who compared VGG16 and VGG19 for rice variety classification, finding VGG19 superior due to its enhanced feature extraction through a more intricate layered structure [16], and by Fendiawati (2023), who achieved strong results with VGG19 in classifying American Sign Language [2]. Furthermore, Iranita (2023) demonstrated the efficacy of CNN-based methods in classifying traditional Batak Tobaulos motifs, reinforcing the applicability of deep learning to traditional fabric patterns [1]. VGG19 advantage likely stems from its deeper network architecture compared to AlexNet. This enables finer extraction of visual details like the complex textures and motifs of quilt fabrics. Support for such architectural benefits appears in Yang *et al.* (2019), who used principal component analysis with deep learning for fabric pilling classification, showing how deeper networks often yield better feature representations [21], and in Marcella *et al.* (2022), who applied VGG19 successfully to eye disease classification with high accuracy [8]. However, VGG19's high computational demand poses a practical challenge, especially on resource-constrained devices, a concern also raised in the comparison of AlexNet and ResNet by Falakhi *et al.* (2022) [15].

Regarding Songket specifically, parallels can be drawn to Amalia *et al.* (2023), who classified Aceh Songket images using a probabilistic neural network, highlighting the need for methods sensitive to intricate visual details in traditional fabrics [14]. Deep learning approaches, as applied through AlexNet and VGG19 here, offer a clear edge in automatically detecting such features over conventional techniques. VGG19 emerges as the better choice for singlet fabric classification based on evaluated performance metrics. Yet, further analysis using confusion matrices could pinpoint specific fabric types prone to misclassification, guiding refinements. Future work might focus on optimizing VGG19 to reduce computational needs or integrating hybrid methods for improved accuracy, as suggested by Hussain *et al.* (2020) in fabric pattern classification [22], and Riana *et al.* (2023), who combined AlexNet with Canny edge detection for image identification [9]. Such efforts could advance the application of deep learning in preserving and recognizing traditional fabrics like sockets through modern tools.

5. Conclusion

The evaluation reveals that VGG19 outperforms AlexNet in classifying singlet fabric types, demonstrating greater effectiveness. This advantage likely stems from VGG19 deep network structure, which enables the extraction of intricate visual features from images. Although the outcomes are encouraging, additional efforts are necessary to enhance model accuracy. Potential improvements include fine-tuning hyperparameters to identify the most effective settings, expanding the dataset to capture a broader range of variations, and implementing advanced data augmentation methods. Such strategies aim to elevate the model's performance, ensuring more precise classification of sandwich fabrics.

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