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Classification of Batik Motifs Using Multi-Texton Co-Occurrence Descriptor and Binarized Statistical Image Features

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Abstract

This study aims to enhance the classification accuracy of batik motifs through a novel integration of Multi-Texton Co-Occurrence Descriptor (MTCD) and Binarized Statistical Image Features (BSIF). The primary objective is to develop a robust feature extraction method that effectively captures both textural and statistical properties of batik images, specifically utilizing the Batik Nitik 960 dataset. Our methodology employs a combination of MTCD and BSIF, followed by Principal Component Analysis (PCA) for dimensionality reduction, optimizing the model's ability to learn from diverse characteristics inherent in batik motifs to augment the diversity and robustness of the training data, we enhanced the Batik Nitik 960 dataset by applying vertical flipping, in addition to existing rotations. We explored three feature fusion approaches: Combination 1, where features are combined before normalization and PCA, achieving an accuracy of 99.948%; Combination 2, where normalization occurs prior to feature combination, also achieving an accuracy of 99.948%; and Combination 3, which applies PCA separately to each feature before combination, resulting in an accuracy of 99.896%. Experimental results demonstrate a remarkable accuracy in classifying these motifs, with the combined MTCD-BSIF features significantly surpassing the individual performances of MTCD at 95.729% and BSIF at 99.531%. This substantial improvement addresses the limitations identified in previous research, which reported an accuracy of only 0.71 on the same dataset. Furthermore, we explore the impact of various feature fusion techniques on classification performance, providing insights into the effectiveness of our proposed methods. Our findings suggest that the combined MTCD-BSIF approach can serve as a benchmark for future studies aiming to enhance classification accuracy in similar domains, thereby contributing to advancements in automated classification systems and their applications across various fields.

Keywords: Batik Nitik, Feature Extraction, Feature Fusion, MTCD, BSIF, SVM

1. Introduction

Batik, an art of textile from Indonesia, has many motifs, each region in Indonesia has its own and each has its meaning [1]. The many and diverse batik patterns in Indonesia are a big challenge in preserving and passing down this heritage; some motifs may be forgotten or left behind in time [2]. This is an even bigger challenge for the public who don't know and can't appreciate the full range of batik designs because they are not familiar with the art [3]. But with the advancement of computer technology and pattern recognition, we can find a solution. By using computer image processing and artificial intelligence, we can build a sophisticated model that can recognize and classify batik fabric motifs. This will help to increase the understanding, appreciation, and preservation of this heritage.

In previous studies, batik motif analysis was possible using the Multi-Texton Co-Occurrence Descriptor (MTCD) and a Support Vector Machine (SVM) for feature extraction and classification. It achieved 0.96 and 1.0 on Batik300 and Batik 41k respectively [4]. However, when the same method was applied to the Batik Nitik 960 dataset, the accuracy dropped to 0.71 [5]. This shows the limitation of generalizability of MTCD and SVM, indicating that it may not be equally effective on all datasets. Therefore, there is a need to explore and implement new feature extraction methods that can enhance classification accuracy and address the challenges of different datasets. By trying new methods, researchers hope to achieve more robust and reliable performance in batik motif classification so that the overall automated batik analysis system can be more effective. Feature extraction methods are very versatile and effective across many fields. For example, in facial similarity studies, Binarized Statistical Image Features (BSIF) were used to

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extract details from facial images [6]. BSIF was chosen for its ability to learn and apply filter sequences autonomously, which makes it better at analyzing and classifying facial features. BSIF was used with Pyramid Multi-Level (PML) and achieved notable accuracy in many datasets: 86.71% in Cornell KinFace, 64.12% in UB KinFace, and 78.89% in KinFaceW-I with SVM as the classifier. BSIF was also used in biometric security systems, especially for palmprint and fingerprint recognition, where it combined with an Extreme Learning Machine (ELM) classifier to achieve a very low Equal Error Rate (EER) of 0.49% [7]. Beyond these applications, BSIF also performed well in iris recognition and yielded good results in datasets such as CASIA-Iris-Syn, Clarkson, MobBIOfake, and CASIA Iris Fake [8]. These examples demonstrate the flexibility and effectiveness of BSIF in various recognition tasks and its potential application in batik motif classification.

The BSIF method for feature extraction uses a set of learned filters derived from natural images [9], which are based on 13 images [10]. These filters vary in size and bit depth: 3×3 with 5–8 bits, 5×5 with 5–12 bits, 7×7 with 5–12 bits, 9×9 with 5–12 bits, 11×11 with 5–12 bits, 13×13 with 5–12 bits, 15×15 with 5–12 bits, and 17×17 with 5–12 bits. This is much more than the MTCD method, which uses 6 types of texton, each of size 2×2.

We classify the data using SVM, which maps the spatial relationships between the various classifications. SVM employs several kernel functions that transform the data into a space with further dimensions before separating and classifying the various classes. Choosing the type of kernel functions—linear, polynomial, sigmoid, or RBF—depends on the characteristics and requirements of the dataset being analyzed [12], [13]. Each kernel has its advantages: linear kernels are good for linearly separable data, polynomial kernels for complex non-linear relationships, sigmoid kernels for data that resembles a neural network, and RBF kernels for flexibility to adapt to different data distributions [14], [15], [16]. The choice of the kernel is crucial to optimize the performance of the SVM and achieve accurate classification results tailored to the data being studied.

In In this study, we combine the Multi-Texton Co-Occurrence Descriptor (MTCD) and BSIF to improve the classification of batik motifs, particularly on the Batik Nitik 960 dataset. We aim to leverage the strengths of both algorithms to overcome the limitations found in previous works. MTCD is effective at capturing texton co-occurrence, while BSIF provides detailed statistical features through learned filters. Additionally, we augmented the Batik Nitik 960 dataset by applying vertical flipping, in addition to the existing rotations present in the dataset, to enhance the model's robustness and generalization capabilities.

2. Method

2.1. Multi Texton Co-Occurrence Descriptor (MTCD)

The MTCD is an advanced version of the Multi Texton Histogram (MTH) feature extraction method that incorporates the Gray Level Co-occurrence Matrix (GLCM) to enhance its capabilities [17], [18]. The MTH part of MTCD uses four types of textons, each 2×2, to analyze textural information. MTCD adds two more types of textons to capture color and edge information [19]. The GLCM component of MTCD facilitates texture analysis through statistical metrics such as Angular Second Moment (ASM), entropy, contrast, and correlation, ensuring comprehensive feature representation [20], [21]. MTCD operates using a sliding window approach, where a texton moves across the image to extract features at different locations. This method allows for localized analysis of textures and colors, enabling the descriptor to capture variations within the image effectively. The combination of textons and statistical measures allows MTCD to provide more comprehensive and detailed feature representation, thus enhancing feature extraction in various image analysis applications [11].

2.2. Binarized Statistical Image Features (BSIF)

The BSIF method operates by convolving an image with a set of filters specifically trained to capture textural and structural information from the image [9]. Convolution is a mathematical operation that involves sliding a filter across the image and computing a weighted sum of the values of the pixels covered by the filter at every position. This process allows the filter to extract features such as edges, textures, and patterns from the image. These filters are pre-trained on natural images to ensure they effectively identify various textures. In simple terms, BSIF works by applying these filters to an image, which results in binary values that reflect the pixel intensities. These binary values are then used to construct histograms, summarizing the distribution of pixel intensities across the image. Each histogram is represented as a 1×10 vector for each bit of the filter, and the combined histogram, when all filters are applied, forms a 1×(filter bit×10) vector. In this paper, we utilize 60 different types of filters, varying in size and bit depth: 3×3 filters with 5–8 bits, 5×5 filters with 5–12 bits, 7×7 filters with 5–12 bits, 9×9 filters with 5–12 bits, 11×11 filters with 5–12 bits, 13×13 filters with 5–12 bits, 15×15 filters with 5–12 bits, and 17×17 filters with 5–12 bits. This extensive range of filter sizes and bit depths enables the BSIF method to capture a broad spectrum of image features, thereby accurately representing and classifying diverse image textures and patterns.

2.3. Scaling

Scaling is an important preprocessing technique in normalizing the distribution of values in a dataset. This technique involves rescaling the data to fit inside a specific range, which is critical for consistency and improving the accuracy of a machine-learning model. The formula in (1) is used for scaling, where 'min' and 'max' represent the smallest and highest boundaries of the feature values, respectively. This method is called MinMaxScaler because it scales the data to a certain pre-defined interval. By doing this, each feature is scaled to the same range which not only maintains the relative proportions of the data but also helps in the convergence and accuracy of the subsequent analysis or classification process. This technique is important when dealing with datasets that have features with different scales or units as it ensures that all the features contribute equally to the analysis.

$$x_s = \frac{x - x_{min}}{x_{max} - x_{min}} \times (\max - \min) + \min \quad (1)$$

2.4. Feature Reduction

Feature reduction is a technique for simplifying data by reducing the number of features when working with large amounts of data. This reduction procedure helps to reduce the complexity of managing and evaluating several features, which improves computing efficiency and model performance. Principal Component Analysis (PCA) is a popular method for feature reduction that uses statistical techniques to convert and condense data into a smaller number of dimensions while maintaining as much original variation as possible. The PCA works by finding the principal components, that are linear combinations of the original features that account for the most variance in the data. By focusing on these principal components, PCA substantially reduces data dimensionality, which is especially useful in reducing overfitting.

PCA was selected for the batik motif classification task due to its ability to preserve significant variance while simplifying the dataset. Additionally, PCA is computationally efficient and can perform faster, making it more suitable for this study. Overall, PCA's effectiveness in handling high-dimensional data and its straightforward implementation make it an ideal choice for this research.

2.5. Support Vector Machine

SVM represent a fundamental approach in the fields of classification and regression, employing statistical techniques to uncover relationships among input variables for predictive modeling. The main objective of SVM is to find a hyperplane that successfully separates classes by maximizing the distance to the closest data points, known as the support vectors. When the data has non-linear properties, SVM transforms it into a higher-dimensional space using kernel approaches such as Radial Basis Function (RBF), polynomial, and sigmoid. This transformation improves classification accuracy by allowing the model to more closely match the dataset's underlying structure. Furthermore, the Batik Nitik 960 dataset utilized in this work is evenly distributed among all classes, ensuring that each motif is well represented and contributing to consistent categorization results.

2.6. Cross-validation

Cross-validation is a statistical approach that evaluates a model's performance and generalizability by separating the given data into numerous subsets known as folds. In this method, the data is separated into n-folds, with each fold serving as a test set and the remaining folds combined to form the set that served as training. For example, if the data is divided into three folds, its model will be trained and tested three times. During every round of iteration, one fold is selected as the testing set, while the other two folds are utilized for training. This strategy assures that all data is used for training and testing only once, resulting in a more reliable assessment of the model's performance on unknown data.

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Cross-validation reduces bias and variance in model evaluation by averaging the findings throughout all iterations, resulting in an improved robust assessment of the model's predictive ability.

3. Feature Fusion

Feature fusion is a method for combining multiple sources of information or features to gain a more detailed and meaningful understanding of the data [14], [15], [16]. This fusion involves combining multiple feature sets to gain more detailed and relevant information. In this study, features were carefully prepared through scaling and Principal Component Analysis (PCA). Scaling using MinMaxScaler was applied to standardize the feature distribution to a fixed range so that the dataset was uniform. PCA is applied to reduce the length of the features and simplify the data while keeping the greatest variance. The fusion of MTCD and Binarized Statistical Image Features (BSIF) was done through different approaches, both extensively and sequentially [7], [17], [18].

Several experimental configurations were tried to find the best way to combine these features. The combination of features was directly named Combination 1, this combination performed the scaling and PCA processes after the features were combined. Combination 1 can be seen in figure 1 (a). The combination of features after the scaling process on each feature is called Combination 2, in this combination PCA was performed after the two features had been combined after the scaling process. Combination 2 can be seen in figure 1 (b). The combination of features after scaling and the PCA process on each feature is called Combination 3. Combination 3 can be seen in figure 1 (c).

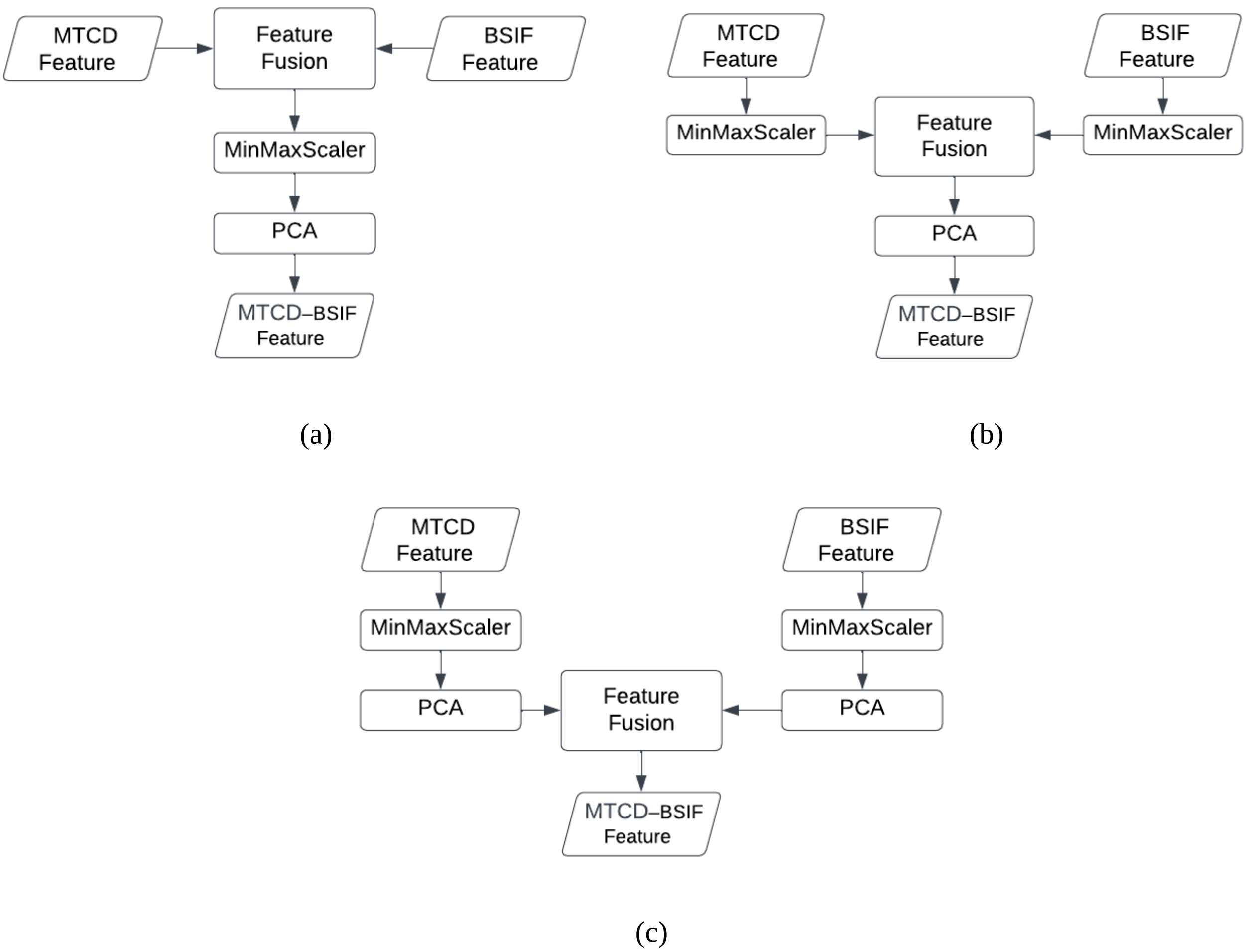

Figure 1. Feature fusion: (a) Combination 1, (b) Combination 2 and (c) Combination 3.

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4. Results and Discussion

This testing is conducted by evaluating the performance of the created model using the accuracy and F1-score parameter.

4.1. MTCD

In the MTCD method, the parameters used are PCA, SVM kernel type, and the value of C in SVM [19]. From these three parameters, sixty test variations are conducted, and then the top ten results are obtained as shown in table 1. The use of 2×2 textons in MTCD is particularly effective for capturing smooth textures in images, allowing MTCD to extract more detailed texture information from the images.

Table 1. The Best Accuracy of MTCD Features

No.	**Feature**	**PCA**	**SVM**		**Accuracy (%)**	**Macro F1-score (%)**
			Kernel	C		
1.	MTCD	0.8	linear	100	95.729 ± 0.865	95.303 ± 0.854
2.	MTCD	N/A	linear	100	95.729 ± 0.865	95.303 ± 0.854
3.	MTCD	0.6	linear	100	95.729 ± 0.865	95.296 ± 0.845
4.	MTCD	0.6	linear	10	95.625 ± 1.141	95.193 ± 1.042
5.	MTCD	0.8	linear	10	95.625 ± 1.141	95.191 ± 1.053
6.	MTCD	N/A	linear	10	95.625 ± 1.141	95.191 ± 1.053
7.	MTCD	0.4	linear	10	95.625 ± 1.259	95.165 ± 1.163
8.	MTCD	0.4	linear	100	95.625 ± 1.169	95.155 ± 1.070
9.	MTCD	N/A	rbf	100	95.521 ± 0.960	95.082 ± 1.023
10.	MTCD	N/A	poly	100	95.208 ± 0.329	94.74 0± 0.244

Table 1 presents the ten highest accuracies achieved by the MTCD feature, clearly demonstrating the critical importance of selecting appropriate parameters for the SVM to attain optimal accuracy. Additionally, the application of PCA for feature reduction significantly enhances the retention of essential information necessary for effective classification.

In this study, PCA was systematically configured to values of 0.2, 0.4, 0.6, and 0.8, corresponding to the retention of 20%, 40%, 60%, and 80% of the original feature variance, respectively. The entries marked as "N/A" indicate instances where PCA was not applied, facilitating a direct and meaningful comparison with the complete feature set. This methodology effectively assesses the extent to which important information is preserved at various levels of variance retention. The results compellingly indicate that high classification accuracy can still be achieved without PCA, affirming that the original features retain sufficient information for effective classification.

While the MTCD method demonstrates exceptional accuracy, the macro F1-score analysis offers critical insights into the model's performance across different classes. The highest accuracy of 95.729% corresponds to a macro F1-score of 95.303% with a standard deviation of ±0.854. The macro F1-score is determined by averaging the F1-scores for each class, treating all classes equally, regardless of size. This statistic offers a balanced assessment of the model's performance, particularly when class distributions are uneven. However, it is essential to acknowledge that certain classes exhibit lower precision and recall, which can result in a slight decline in the F1-score. This variability in performance underscores the necessity of considering both accuracy and F1-score when comprehensively evaluating model performance. Furthermore, configurations that incorporate PCA yield slightly improved macro F1-scores, indicating that dimensionality reduction effectively retains important features, thereby enhancing classification performance. This analysis highlights the importance of conducting thorough error analysis to identify specific classes that require further attention and improvement. The complete test data can be accessed at https://bit.ly/___mtcd.

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4.2. BSIF

In the BSIF method, the parameters used are Filter, PCA, SVM Kernel and SVM C. Based on these parameters, 3600 test variations are conducted. Evaluation is then performed on the accuracy obtained from these parameters, and the top 10 results are shown in table 2.

Table 2. The Best Accuracy of BSIF Features

No.	Feature	Filter		PCA	SVM		Accuracy (%)	Macro F1-score (%)
		Size	Bit		Kernel	C		
1.	BSIF	17x17	10	0.6	rbf	10	99.531 ± 0.400	99.529 ± 0.403
2.	BSIF	17x17	10	0.6	rbf	100	99.531 ± 0.400	99.529 ± 0.403
3.	BSIF	17x17	10	0.8	rbf	10	99.479 ± 0.376	99.476 ± 0.378
4.	BSIF	17x17	10	N/A	rbf	10	99.479 ± 0.376	99.476 ± 0.378
5.	BSIF	17x17	10	0.8	rbf	100	99.479 ± 0.376	99.476 ± 0.378
6.	BSIF	17x17	10	N/A	rbf	100	99.479 ± 0.376	99.476 ± 0.378
7.	BSIF	17x17	10	N/A	rbf	1	99.427 ± 0.271	99.421 ± 0.275
8.	BSIF	17x17	10	0.8	rbf	1	99.427 ± 0.400	99.421 ± 0.406
9.	BSIF	17x17	10	0.8	linear	10	99.375 ± 0.295	99.372 ± 0.297
10.	BSIF	17x17	10	N/A	linear	10	99.375 ± 0.295	99.372 ± 0.297

Table 2 presents the top ten accuracies achieved using BSIF features, clearly demonstrating that the choice of filters significantly impacts accuracy. The 17 × 17 filter, which captures coarse patterns in batik motifs, outperforms smaller filters that focus on finer details. The wide range of filter sizes has a direct effect on the quality of texture representation; smaller filter sizes yield smoother textures, while larger filter sizes capture rougher textures. Additionally, larger bit depths allow for more filters to be used, which in turn extracts more features from the image. However, an excessive number of features can lead to a decrease in accuracy, so it is crucial to find a sweet spot to achieve the optimum filter size and bit depth.

Additionally, the selection of the SVM kernel is crucial for enhancing accuracy, while the C value in SVM serves as a significant hyperparameter that improves performance when the features are adequately prepared. The application of PCA for feature reduction is vital for preserving essential information, with PCA set to retain 60% and 80% of the original feature variance. The "N/A" entries indicate instances where PCA was not applied, facilitating a meaningful comparison with the complete feature set.

While the BSIF method achieves exceptional accuracy, the macro F1-score analysis reveals important insights into class performance. The highest accuracy of 99.531% corresponds to a macro F1-score of 99.529% with a standard deviation of ±0.403, indicating strong overall performance. However, certain classes may exhibit lower precision and recall, leading to a slight decline in the F1-score. This variability highlights the need to consider both accuracy and F1-score in evaluating model performance comprehensively. Furthermore, configurations incorporating PCA yield improved macro F1-scores, demonstrating that dimensionality reduction effectively retains important features and enhances classification performance. This analysis underscores the importance of thorough error analysis to identify specific classes requiring further attention and improvement. The complete test data can be accessed at https://bit.ly/___bsif.

4.3. Combination 1 MTCD–BSIF

In the Combination 1 method for MTCD–BSIF features, the parameters used include Filter, PCA, SVM Kernel, and SVM C. Using these parameters, 3,600 test variations were conducted. The accuracy results from these tests were evaluated, and the top 10 outcomes are presented in table 3.

Table 3. The Best Accuracy of Combination 1 method for MTCD–BSIF features

No.	Feature	Filter		PCA	SVM		Accuracy (%)	Macro
		Size	Bit		Kernel	C		F1-score (%)
1.	MTCD-BSIF	17x17	7	0.6	linear	1	99.948 ± 0.090	99.948 ± 0.091
2.	MTCD-BSIF	17x17	7	0.8	linear	1	99.948 ± 0.090	99.948 ± 0.091
3.	MTCD-BSIF	17x17	7	N/A	linear	1	99.948 ± 0.090	99.948 ± 0.091
4.	MTCD-BSIF	17x17	7	N/A	rbf	10	99.948 ± 0.090	99.948 ± 0.091
5.	MTCD-BSIF	17x17	7	N/A	rbf	100	99.948 ± 0.090	99.948 ± 0.091
6.	MTCD-BSIF	17x17	6	0.6	linear	1	99.896 ± 0.104	99.895 ± 0.105
7.	MTCD-BSIF	17x17	6	0.8	linear	1	99.896 ± 0.104	99.895 ± 0.105
8.	MTCD-BSIF	17x17	6	N/A	linear	1	99.896 ± 0.104	99.895 ± 0.105
9.	MTCD-BSIF	17x17	7	N/A	poly	1	99.896 ± 0.104	99.895 ± 0.105
10.	MTCD-BSIF	17x17	7	N/A	poly	10	99.896 ± 0.104	99.895 ± 0.105

Table 3 presents the ten best accuracies achieved using the Combination 1 method for MTCD–BSIF features. The results indicate that the choice of filters during the BSIF feature extraction process significantly impacts accuracy. The optimal performance is achieved with a 17 × 17, 7-bit filter, demonstrating that the combination of fine features from MTCD and coarse features from BSIF effectively enhances accuracy.

The macro F1-score analysis reveals that the highest accuracy of 99.948% corresponds to a macro F1-score of 99.948% with a standard deviation of ±0.091, indicating that the model performs exceptionally well across all classes. This high macro F1-score suggests that the model maintains a balanced performance, ensuring that precision and recall are consistently high across different classes. While the selection of the SVM kernel is crucial for improving performance, the C value in SVM serves as an important hyperparameter that enhances accuracy, particularly when the features are adequately prepared. Additionally, the application of PCA for feature reduction is instrumental in retaining important information necessary for the classification process. The complete test data can be accessed at https://bit.ly/___com1.

4.4. Combination 2 MTCD–BSIF

In the Combination 2 method for MTCD–BSIF features, the parameters used include Filter, PCA, SVM Kernel, and SVM C. Using these parameters, 3,600 test variations were conducted. The accuracy results from these tests were evaluated, and the top 10 outcomes are presented in table 4.

Table 4. The Best Accuracy of Combination 2 method for MTCD–BSIF features

No.	Feature	Filter		PCA	SVM		Accuracy (%)	Macro
		Size	Bit		Kernel	C		F1-score (%)
1.	MTCD-BSIF	17x17	7	0.6	linear	1	99.948 ± 0.090	99.948 ± 0.091
2.	MTCD-BSIF	17x17	7	0.8	linear	1	99.948 ± 0.090	99.948 ± 0.091
3.	MTCD-BSIF	17x17	7	N/A	linear	1	99.948 ± 0.090	99.948 ± 0.091
4.	MTCD-BSIF	17x17	7	N/A	rbf	10	99.948 ± 0.090	99.948 ± 0.091
5.	MTCD-BSIF	17x17	7	N/A	rbf	100	99.948 ± 0.090	99.948 ± 0.091
6.	MTCD-BSIF	17x17	6	0.6	linear	1	99.896 ± 0.104	99.895 ± 0.105
7.	MTCD-BSIF	17x17	6	0.8	linear	1	99.896 ± 0.104	99.895 ± 0.105
8.	MTCD-BSIF	17x17	6	N/A	linear	1	99.896 ± 0.104	99.895 ± 0.105

No.	Feature	Filter		PCA	SVM		Accuracy (%)	Macro
		Size	Bit		Kernel	C		F1-score (%)
9.	MTCD-BSIF	17x17	7	N/A	poly	1	99.896 ± 0.104	99.895 ± 0.105
10.	MTCD-BSIF	17x17	7	N/A	poly	10	99.896 ± 0.104	99.895 ± 0.105

Table 4 presents the ten best accuracies achieved using the Combination 2 method for MTCD–BSIF features. The complete test data can be accessed at https://bit.ly/___com2. Table 4 demonstrates that the filters used during the BSIF feature extraction process have an important effect on reaching the best accuracy. Using a 17 x 17 filter, the combination of fine features from MTCD and coarse features from BSIF yields the highest accuracy of 99.948% with a standard deviation of ±0.091, indicating its effectiveness. While the selection of the SVM kernel plays an important role in improving accuracy, the SVM C parameter has a less significant effect. Meanwhile, feature reduction using PCA helps retain important information for the classification process.

4.5. Combination 3 MTCD–BSIF

In the Combination 3 method for MTCD–BSIF features, the parameters used include Filter, PCA, SVM Kernel, and SVM C. Using these parameters, 3,600 test variations were conducted. The accuracy results from these tests were evaluated, and the top 10 outcomes are presented in table 5.

Table 5. The Best Accuracy of Combination 3 method for MTCD–BSIF features

No.	Feature	Filter		PCA	SVM		Accuracy (%)	Macro
		Size	Bit		Kernel	C		F1-score (%)
1.	MTCD-BSIF	17x17	7	0.8	linear	1	99.948 ± 0.090	99.948 ± 0.091
2.	MTCD-BSIF	17x17	7	N/A	linear	1	99.948 ± 0.090	99.948 ± 0.091
3.	MTCD-BSIF	17x17	7	N/A	rbf	10	99.948 ± 0.090	99.948 ± 0.091
4.	MTCD-BSIF	17x17	7	N/A	rbf	100	99.948 ± 0.090	99.948 ± 0.091
5.	MTCD-BSIF	17x17	6	0.6	linear	1	99.896 ± 0.104	99.895 ± 0.105
6.	MTCD-BSIF	17x17	6	N/A	linear	1	99.896 ± 0.104	99.895 ± 0.105
7.	MTCD-BSIF	17x17	7	0.6	linear	1	99.896 ± 0.104	99.895 ± 0.105
8.	MTCD-BSIF	17x17	7	N/A	poly	1	99.896 ± 0.104	99.895 ± 0.105
9.	MTCD-BSIF	17x17	7	0.6	linear	10	99.896 ± 0.104	99.895 ± 0.105
10.	MTCD-BSIF	17x17	7	N/A	poly	10	99.896 ± 0.104	99.895 ± 0.105

Table 5 presents the ten best accuracies achieved using the Combination 3 method for MTCD–BSIF features. The results indicate that the choice of filters during the BSIF feature extraction process significantly impacts accuracy. The optimal performance is achieved with a 17 × 17, 7-bit filter, demonstrating that the combination of fine features from MTCD and coarse features from BSIF effectively enhances accuracy.

The macro F1-score analysis reveals that the highest accuracy of 99.948% corresponds to a macro F1-score of 99.948% with a standard deviation of ±0.091, indicating exceptional performance across all classes. This high macro F1-score suggests that the model maintains a balanced performance, ensuring high precision and recall across different classes. While the selection of the SVM kernel is crucial for improving performance, the C value in SVM serves as an important hyperparameter that enhances accuracy, particularly when the features are adequately prepared. Additionally, the application of PCA for feature reduction is instrumental in retaining important information necessary for the classification process. The complete test data can be accessed at https://bit.ly/___com3.

4.6. Combination result

The average accuracy results indicate that Combination 1 (88.006%) slightly outperforms Combination 2 (88.004%) and significantly surpasses Combination 3 (87.915%). This difference can be attributed to the processing methods of the MTCD and BSIF features. In Combination 1, features are combined first, preserving their relationships before normalization and PCA, allowing for effective capture of both individual and joint variance.

In Combination 2, normalization occurs before combining the features, which may weaken inter-feature relationships and lead to slightly lower average accuracy. Combination 3 performs the worst, as PCA is applied separately to each feature before combining, eliminating inter-feature relationships and limiting the capture of meaningful variance. The small performance difference between Combinations 1 and 2 likely arises from PCA's sensitivity to data scaling and minor numerical variations. Overall, Combination 1 retains feature interactions more effectively, resulting in the highest average accuracy.

4.7. Support Vector Machine

The following bar graph provides a visual representation of the average accuracy achieved by various kernel types linear, RBF, sigmoid, and polynomial across different classification methods, including MTCD, BSIF, Combination 1, Combination 2, and Combination 3. This analysis aims to illustrate the effectiveness of each kernel in enhancing classification performance and to highlight the advantages of feature combination techniques in SVM. Figure 2 illustrates the average accuracy for different kernel types (linear, Radial Basis Function (RBF), sigmoid, and polynomial) using various methods (MTCD, BSIF, Combination 1, Combination 2, and Combination 3).

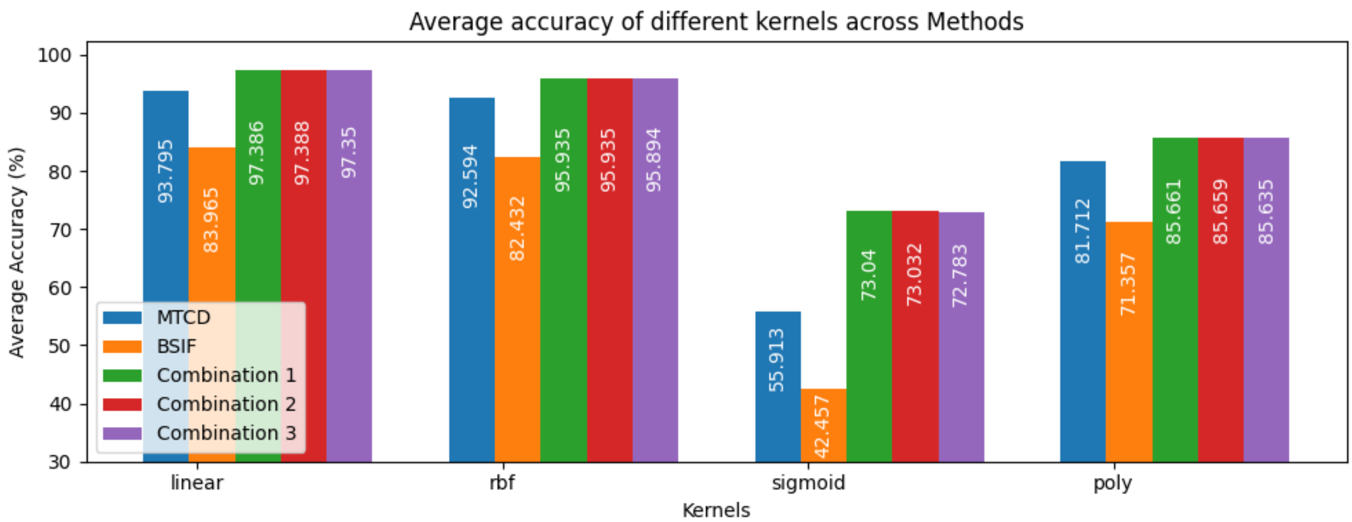

Figure 2. Kernel comparison

The selection of an SVM kernel is critical for improving performance, with different kernels displaying varying degrees of success across approaches. These findings reveal that linear and RBF kernels regularly attain the maximum accuracy, demonstrating their superiority in classification tasks. In contrast, the sigmoid kernel demonstrates significantly lower accuracy, particularly in the MTCD and BSIF methods. Combination 1 and Combination 2 consistently outperform other approaches across all kernels, suggesting that integrating features from MTCD and BSIF enhances classification results. While the polynomial kernel performs competitively, it generally yields lower accuracy than the linear and RBF kernels, with the BSIF method showing the lowest accuracy overall. Additionally, the C parameter in SVM serves as a crucial hyperparameter that, when appropriately tuned, further enhances accuracy by influencing the margin and decision boundary, particularly when the features are well-prepared. This graph highlights the combined importance of kernel selection and hyperparameter tuning in optimizing SVM performance and reinforces the advantage of feature fusion for improved classification accuracy.

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4.8. Future Works

Future research should focus on developing a real-time batik classification system for quality control and inventory management in the batik industry. This will involve optimizing current models for computational efficiency to ensure rapid image processing. Additionally, exploring advanced preprocessing techniques and data augmentation strategies will enhance the robustness of classification models against noise and imperfections in batik patterns.

While this study reveals great accuracy, it is important to address the computing efficiency of the methods used. A discussion on processing time, memory usage, and scalability would be beneficial for real-time applications. Although specific measurements were not included, the methods employed are effective and can be optimized through parallel processing. By focusing on these areas, future researchers might improve batik classification technologies, making them more durable and relevant in real-world situations. Future work could explore comparisons with state-of-the-art techniques for a more comprehensive analysis.

5. Conclusion

The results of the augmentation of the Batik Nitik 960 dataset using MTCD, BSIF, and their combination (MTCD–BSIF) show that the combined features achieve the highest accuracy of 99.948%. BSIF alone attained an accuracy of 99.531%, while MTCD achieved 95.729%. Notably, BSIF can outperform MTCD; however, when combined, the two methods yield significantly better accuracy than either MTCD or BSIF alone in the Batik Nitik 960 dataset. The analysis indicates that BSIF performs better with larger filter sizes, as evidenced by the optimal results obtained with a 17×17 filter. The wide range of filter sizes for BSIF has a direct effect on the quality of texture representation; smaller filter sizes yield smoother textures, while larger filter sizes capture rougher textures. Furthermore, the combination of small and large textons or filters using MTCD and BSIF demonstrates better accuracy than MTCD and BSIF individually. Additionally, Combination 1 demonstrates superior accuracy compared to Combinations 2 and 3, as it preserves the raw relationships between features before applying feature-wise normalization and PCA. The application of a linear kernel for the Support Vector Machine (SVM) successfully isolates the extracted features, yielding impressive accuracy. The C value in SVM serves as a crucial hyperparameter, enhancing accuracy when the features are adequately prepared. Overall, these findings underscore the robustness of the feature combination and the importance of parameter selection in achieving optimal classification performance.

6. Declarations

6.1. Author Contributions

Conceptualization: A.R.M., S., and D.A.T.; Methodology: S.; Software: A.R.M.; Validation: A.R.M., S., and D.A.T.; Formal Analysis: A.R.M., S., and D.A.T.; Investigation: A.R.M.; Resources: S.; Data Curation: S.; Writing Original Draft Preparation: A.R.M., S., and D.A.T.; Writing Review and Editing: S., A.R.M., and D.A.T.; Visualization: A.R.M. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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