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Utilizing convolutional neural networks for the classification and preservation of Kalinga textile patterns

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ABSTRACT

This study introduces a system that utilizes Convolutional Neural Networks (CNN) to categorize Kalinga textiles in a structured manner. The main objective is to systematically identify and name the patterns found in these textiles. The research uses a dataset that includes ten different categories of Kalinga textiles. Metrics such as accuracy, precision, recall, and F1 Score are used to assess the performance of the system. The outcomes demonstrate high precision values between 0.8 and 1.00, showcasing the model's proficiency in precisely classifying and labeling the patterns of Kalinga textiles. Similarly, the recall values, which vary from 0.75 to 1.00 for each category, underscore the model's effectiveness in categorization. These results highlight the system's capability to recognize and categorize Kalinga textiles, with recall values providing strong evidence of its reliability. F1 scores, which consider both precision and recall, range from 0.86 to 0.97 across the categories, indicating the model's accuracy in classification. The introduced technique for image identification shows promise for identifying and categorizing Kalinga textiles, thereby contributing to the preservation and promotion of this cultural heritage. It offers a valuable tool for researchers, enthusiasts, and cultural institutions. Future research could focus on expanding the dataset to improve the model's robustness and exploring its application to other areas of textiles. Continuous enhancements to the model, based on user feedback and technological advancements, will ensure its ongoing effectiveness and relevance.

1. Introduction

The process of textile manufacturing is lengthy and involves transforming synthetic fibers into yarns and fabrics through weaving (Wang et al., 2023). Kalinga is proud of its heritage and deep-rooted weaving traditions. The textiles made in Kalinga have both practical and artistic value, showcasing the skill and ingenuity of local weavers. In the Kalinga region, textile making is primarily a women's occupation. Communities such as Bontok, Ifugao, Kalinga, Tinguian, Kankanaey, Apayao, and Ibaloy each have unique textile styles and patterns. These creations are influenced by beliefs, socio-political factors, and artistic expressions, which contribute to their origins, purposes, and cultural significance.

According to Kelly (2022), younger women are increasingly interested in textile weaving, which may help preserve the various techniques, patterns, and traditional practices associated with textile production in the region. However, the production of these textiles is at risk of disappearing due to the growing prevalence of mass-produced clothing.

To protect and preserve Kalinga's heritage, extensive academic research has explored the application of machine learning techniques for identifying and classifying textiles. A benchmarking approach was used to comprehensively assess the proposed image recognition system for Kalinga textiles. This involved evaluating the results by comparing them with findings from other published papers in the field of textile recognition and classification. By leveraging established benchmarks, the researchers assessed the performance of their study against existing state-of-the-art models, providing a valuable framework for validating the effectiveness and innovation of the new approach within the broader context of textile identification research.

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The works by Abel et al. (2022), Alagao et al. (2018), Balbin et al. (2016), De Los Reyes et al. (2016), and Ostia et al. (2019) demonstrated the use of image processing in domains, including industrial image processing, texture classification, medical imaging like x-rays real-time imaging, object recognition, text recognition, and the textile industry.

The technique used in this study involved binarization to differentiate between the background and the presence of textile pilling. A fabric database was created using morphological and topological image processing techniques to extract features from the image data. Artificial neural networks (ANN) and support vector machines (SVM) were utilized to address the issue of grading textiles. Since textiles have varying properties, it is essential to have subjective evaluations.

Several research studies have explored versions of Convolutional Neural Networks (CNN) and YOLO V3 to detect objects in types of media like images. The study of Elabbas et al. (2021) reported a 75% accuracy rate when examining 20 images of AOM, CSOM, and normal tympanic membrane. CNN research has also focused on recognizing kinds of fruits, evaluating abnormalities, and exploring agricultural domains. Studies by Cruz et al. (2023), Antolin et al. (2021), Manlises et al. (2023), Desiderio et al. (2022), Tenorio et al. (2022) and Sanchez et al. (2023) further support the use of methods for disease classification in fruits using neural networks, clustering, and color-based segmentation techniques. Their research aims to examine approaches for identifying illnesses in fruit varieties.

Various studies conducted by Uy and Villaverde (2021), Al Gallenero and Villaverde (2023), Padilla et al. (2020), Mateo et al. (2022), Buenconsejo and Linsangan (2021), and Muhali and Linsangan (2022) have explored types of fruits. The conclusion was reached that CNN is an effective technique for disease detection in fruits. These characteristics are then utilized to train the computing approach network.

Additionally, the research carried out by Luis et al. (2022), Santo et al. (2022), Cruz et al. (2017), and Hong and Caya (2022) have investigated the application of image processing techniques in agriculture aiming to provide readers with an understanding of the advantages and limitations associated with vision-based systems.

One major challenge in the textile industry is textile pilling, which affects the appearance of garments. Manickam et al. (2019) aimed to evaluate pilling characteristics to determine textile quality using discrete Fourier transform and Gaussian methods. The issue of grading textiles was specifically addressed by Behera (2004), who used ANN and SVM for this purpose.

Furthermore, extensive research has been conducted on various topics, including studying the structure of fibers, estimating cotton maturity, quantifying impurities in cotton, analyzing pore size distribution, evaluating thread unevenness, examining fiber crimp, studying fiber blending techniques, determining different types of weaves, identifying fabric flaws, measuring shrinkage levels, assessing fabric wrinkles, evaluating carpet appearance, and detecting seam imperfections.

The utilization of CNN for textile recognition and classification has been explored by Chen et al. (2019), Huang and Fu (2018), Siregar and Octariadi (2019), Iqbal Hussain et al. (2020), and Turkut et al. (2020) as documented in literature sources. However, it is important to acknowledge the research on identifying and categorizing Kalinga textiles specifically. These textiles are renowned for their patterns and designs, which set them apart from other types of fabrics. Henceforth, CNNs present a complex opportunity for textile identification and categorization purposes.

Moreover, this study aims to contribute to the broader field of textile identification and categorization by applying advanced deep-learning techniques. It specifically focuses on using CNNs to recognize textiles within a non-Western cultural context, highlighting both the challenges and opportunities. Assessing the effectiveness of machine learning systems in identifying Kalinga textile patterns is crucial.

The primary goal of this research is to create an Image Recognition System for Kalinga Textiles by utilizing image processing techniques with CNNs. The study aims to classify ten specific textiles from the Kalinga region: a) Bilallikted, b) Ilaglis, c) Kayaw, d) Kilayaw, e) Lilabey, f) Pilagpageyn, g) Pilaslang, h) Silaksakaw, i) Silambituwon, and j) Sulugwid. The objectives include evaluating the system's performance by measuring its accuracy, precision, recall, and F1 Score. Additionally, the research aims to develop a hardware device using Raspberry Pi to identify patterns by capturing images through a camera. A confusion matrix will be used to comprehensively evaluate the model's effectiveness.

This research is important for the Kalinga population as it preserves and documents their cultural history and textile industry by digitizing and archiving Kalinga textile patterns for future generations to access and appreciate. Travelers can also benefit from this feature by easily identifying the name or origin of a textile. The study provides a framework for future researchers to integrate textile recognition in various fields.

The focus of this study is solely on analyzing the patterns within each textile without evaluating their quality. The system will concentrate on identifying and categorizing Kalinga textiles. However, it should be noted that the model does not support a spoofing strategy, which may affect its ability to accurately identify and classify textiles.

2. Materials and methods

The CNN model was implemented on a Raspberry Pi 4 to recognize Kalinga textiles. The setup included connecting a 5-inch LCD screen to the Raspberry Pi and configuring the camera module. Data from Kinwa Etnika Handicrafts were collected, processed, and labeled for ten types of textiles. Jupyter notebooks were used for software development and code execution. The CNN architecture consisted of three convolutional layers and two fully connected layers. The model was saved during training whenever there was an improvement after ten epochs. The performance of the model was evaluated using metrics such as accuracy, precision, recall, and F1 score. Once validated, the model was ready for deployment for textile recognition purposes. The following details outline the conduct of the experiments.

2.1. Block diagram

The Raspberry Pi 4 hosted the deployed model for processing input images, while the initial training occurred on a personal computer. Textile pattern images were captured using the Raspberry Pi Camera, with user control and image classification displayed on a 5'' LCD. Refer to Fig. 1 for the block diagram.

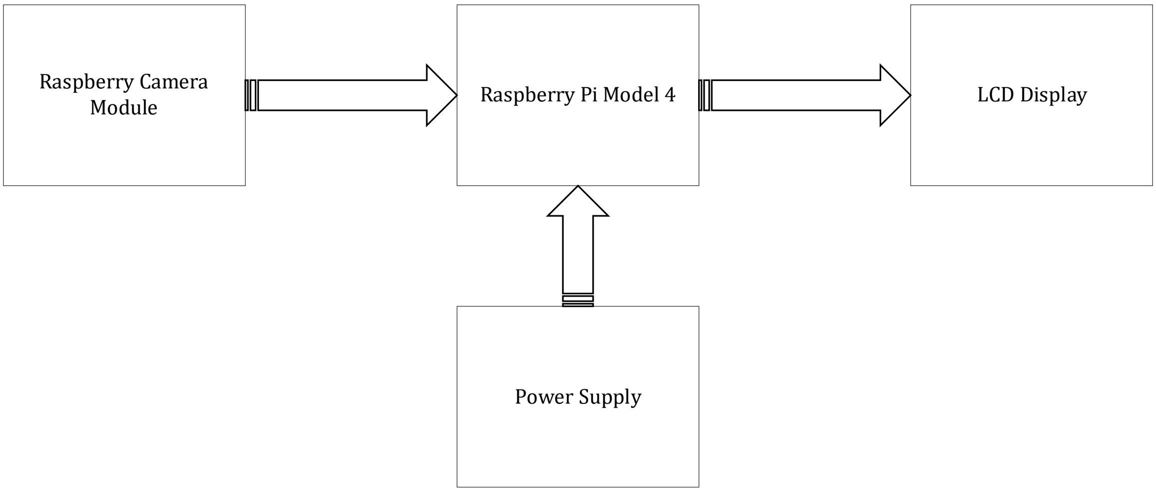

Fig. 1: Block diagram of the Kalinga textile recognition using CNN

2.2. Hardware setup

The HDMI 1 port of the Raspberry Pi connected to the LCD, drawing power from one of the USB ports. The camera module is linked to its designated port, and a 32GB microSD is inserted into the Raspberry Pi's microSD slot. Power was supplied through the Micro USB power port. Refer to Fig. 2 for the project's hardware setup. Notably, limitations include power supply constraints, potential interruptions, and the need for model updates in future research.

2.3. Data

The data was collected from Kinwa Etnika Handicrafts, owned by Mrs. Florence A. Ao-wat, a well-known weaving center in Kalinga. A total of 6,480 data points were gathered and augmented to create a total of 16,504 datasets. These datasets were labeled for ten different types of textiles used by the people of Kalinga. The data was divided into three categories: training, testing, and validation. The training set comprised 80% of the data, while the testing and validation sets each consisted of 10%. The augmentations included 20-degree rotations, horizontal and vertical flips, zoom range, and color adjustments.

The images underwent preprocessing and augmentation, which involved labeling them according to their respective classes and applying techniques such as rotation and flipping to increase the dataset's diversity. Figs. 3 and 4 show examples of preprocessed images.

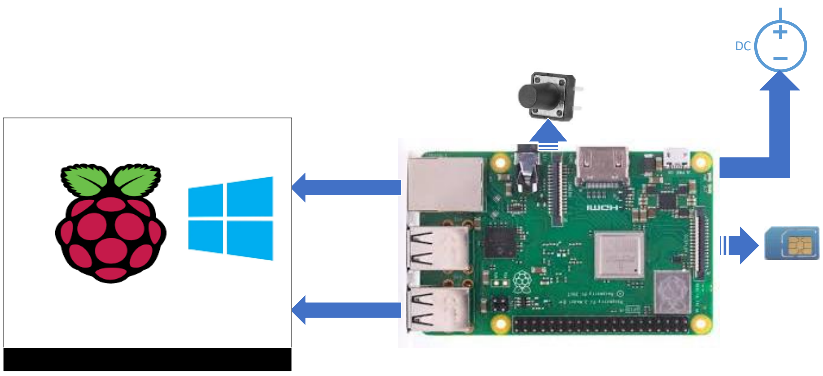

Fig. 2: Hardware setup of the Kalinga textile recognition using CNN

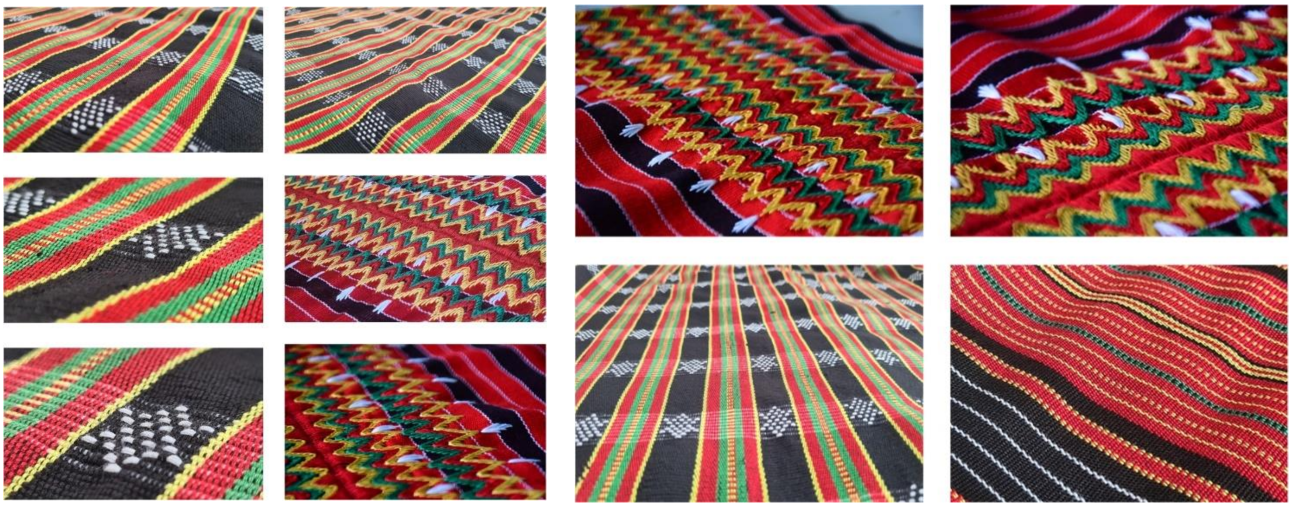

Fig. 3: Sample data of the Kalinga textile recognition using CNN

2.4. Software development

Jupyter was used to perform various processes in the project. It facilitated iteration analysis and the design process using programming languages, allowing for direct expression through array mathematics and matrices. Jupyter notebooks provided an interactive environment where the researcher could write and execute code directly within cells.

2.5. Model development and architecture

The CNN architecture was used for textile recognition. The model's performance was optimized by adjusting various hyperparameters and applying regularization techniques. Data augmentation and rescaling layers were used before the main model for image preprocessing. The model included three convolutional layers as shown in Fig. 5:

- Conv2D layer with 16 filters, a kernel size of 3x3, 'same' padding, and ReLU activation.
- MaxPooling2D layer for max pooling operation.
- Conv2D layer with 32 filters, a kernel size of 3x3, 'same' padding, and ReLU activation.
- Another MaxPooling2D layer.
- Conv2D layer with 64 filters, a kernel size of 3x3, 'same' padding, and ReLU activation.
- Final MaxPooling2D layer.

The flattened layer converted the 2D feature maps from the convolutional layers into a 1D vector for the fully connected layers. The model also included two fully connected layers:

- A dense layer with 128 units and ReLU activation.
- A dense layer with a number of units equal to the number of classes (output size) and softmax activation to represent class probabilities.

Fig. 4 shows the source code for the data augmentation used in the CNN model for Kalinga Textile Recognition.

2.6. Training and evaluation

The dataset was divided into training and testing sets. The model was compiled using the 'Adam' optimizer, which is suitable for deep learning models. SparseCategoricalCrossEntropy was used as the loss function for multi-class classification. The model's accuracy was monitored during training, which was conducted over ten epochs. The model was saved whenever there was an improvement.

The CNN model was trained using the training set, and its performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. Iterative training and refinement were performed to enhance the model's performance. Fig. 5 shows the source code for the Model Training and Validation of the Kalinga Textile Recognition Using CNN.

```
model = keras.Sequential([
  data_augmentation,
  keras.layers.experimental.preprocessing. Rescaling (1./255),
  keras.layers.Conv2D (16, 3, padding='same', activation='relu'),
  keras.layers.MaxPooling2D(),
  keras.layers.Conv2D (32, 3, padding='same', activation= 'relu'),
  keras.layers.MaxPooling2D(),
  keras.layers.Conv2D (64, 3, padding='same', activation='relu'),
  keras.layers.MaxPooling2D(),
  keras.layers.Flatten(),
  keras.layers.Dense (128, activation='relu'),
  keras.layers.Dense (num_classes, activation='softmax')
])
```

Fig. 4: CNN model of the Kalinga textile recognition using CNN

```
model.compile(optimizer='adam',
          loss=tf.keras. losses.SparseCategoricalCrossentropy(),
               metrics=['accuracy'])

epochs = 10
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs epochs,
  callbacks=[checkpoint_callback]
)
```

Fig. 5: Model training and validation of the Kalinga textile recognition using CNN

2.7. Validation and deployment

Once the model achieved satisfactory performance, it was validated using a separate validation set or cross-validation techniques. The validation process used the designated validation dataset. Fig. 6 shows the source code for the validation and deployment of the Kalinga Textile Recognition model using CNN.

3. Results and discussions

This section includes the interpretation of the data, the analysis of the results, and the discussion of those results. The findings are presented in Table 1 and Figs. 7 and 8, along with explanations and discussions. Solutions to the specific issues raised by the research aims are also provided. Fig. 7 shows the graph of the training and validation accuracy of the algorithm used.

The training accuracy improves steadily from 0.4065 to 0.9853 over ten epochs, indicating that the model effectively learns the patterns and features in the training data. Meanwhile, the validation accuracy, which measures the model's ability to generalize to new, unseen data, increases from 0.5157 to 0.8987. Although slightly lower than the training accuracy, the upward trend in validation accuracy suggests that the model has potential for generalizing new data well. Fig. 8 shows the training and validation loss.

The training loss, as shown in Fig. 8, steadily decreases from 1.6937 to 0.0502 throughout the training process. This indicates that the model is effectively reducing the difference between its predictions and the actual labels in the training data. Similarly, the validation loss, which measures the model's performance on unseen data, fluctuates between 0.1882 and 1.5402. While a decreasing trend in validation loss is desirable, the higher loss values in certain epochs suggest challenges in generalization. Table 1 displays the Precision, F1-score, and Recall results of the model.

```
for images, labels in val_ds:
   predictions = model.predict(images)
   predicted_labels.extend(np.argmax(predictions, axis=1))
   actual_labels.extend(labels.numpy())

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss history.history['val_loss']
```

Fig. 6: Validation of the model

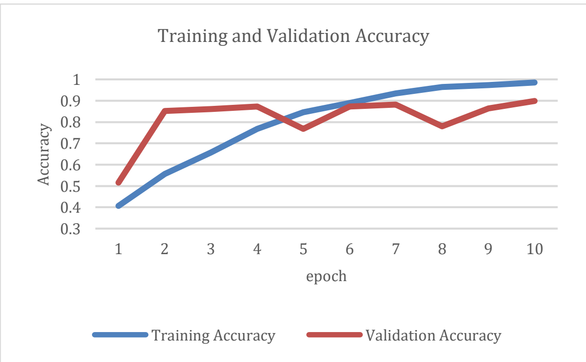

Fig. 7: Training and validation accuracy of the model

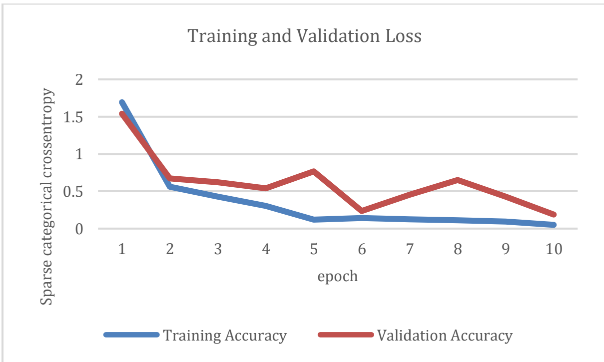

Fig. 8: Training and validation loss

Table 1 shows the classification metrics, including precision, recall, and F1-score, for each class. The classification model was evaluated on a dataset with 541 instances across multiple classes.

- Precision: Ranged from 0.8 to 1.00, indicating high accuracy in correctly predicting instances for each textile class. For example, Bilalikted, Kayaw, Kilayaw, Lilabey, Pilagpageyn, Silambituwon, and

Sulugwid achieved precision scores of 0.94, 0.95, 1.00, 1.00, 0.93, 1.00, and 0.98 respectively, showing a low rate of false positives for these classes.

- Recall: Ranged from 0.75 to 1.00, reflecting the model's ability to correctly identify instances belonging to each class. Ilaglis and Silaksakaw textiles had perfect recall scores of 1.00, indicating excellent identification accuracy for these classes.
- F1-Score: Ranged from 0.86 to 0.97, highlighting the model's robust performance across different classes. For instance, Kayaw, Kilayaw, and Sulugwid had F1 scores of 0.97, 0.95, and 0.95, respectively, demonstrating high accuracy and reliability in predictions for these classes.

The model's overall accuracy was 0.95, indicating that most instances in the dataset were correctly predicted by the model. This demonstrates the effectiveness of the classification model in accurately categorizing instances into their respective classes. Fig. 9 shows the performance of the model using a confusion matrix.

Table 1: Precision, F1-score, and recall results of the model

Class	Precision	F1-score	Recall
Bilalikted	0.94	0.91	0.92
Ilaglis	0.83	1	0.91
Kayaw	0.95	0.98	0.97
Kilayaw	1	0.9	0.95
Lilabey	1	0.75	0.86
Pilagpageyn	0.93	0.96	0.94
Pilaslang	0.88	0.96	0.92
Silaksakaw	0.8	1	0.89
Silambituwon	1	0.82	0.9
Silugwid	0.98	0.93	0.95

TRUE \ PREDICTED	BILALIKTED	ILAGLIS	KAYAW	KILAYAW	LILABEY	PILAGPAGEYN	PILASLANG	SILAKSAKAW	SILAMBITUWON	SILUGWID
BILALIKTED	52	0	0	0	0	1	0	0	0	3
ILAGLIS	0	49	0	0	0	0	0	0	0	0
KAYAW	0	0	54	0	2	0	3	0	0	0
KILAYAW	3	0	0	37	0	0	2	0	0	1
LILABEY	1	0	3	0	51	1	2	2	0	0
PILAGPAGEYN	0	0	0	0	0	49	1	0	0	0
PILASLANG	0	0	0	0	0	1	55	1	1	1
SILAKSAKAW	0	1	0	0	0	0	2	66	0	0
SILAMBITUWON	0	11	0	0	0	0	0	2	37	0
SILUGWID	0	4	0	0	0	4	2	0	0	38

Fig. 9: Performance of the model using a confusion matrix

The diagonal elements of the confusion matrix indicate that the model accurately predicted many types of textiles. For example, "Bilalikted" had a precision of 0.953, with 53 out of 54 instances correctly identified. Similarly, "Ilaglis" correctly predicted all 49 cases, achieving perfect precision and recall. These results demonstrate the model's strong ability to differentiate between these classes.

However, Fig. 9 also shows some misclassifications. This suggests that there might be similarities or overlapping features among these classes, leading to errors. For instance, "Silambituwon" had eleven instances incorrectly predicted as "Ilaglis." Further research on distinguishing characteristics of these classes could help improve the model's performance. Additionally, these errors may be due to the inherent complexity or ambiguity in the data. Table 2 compares the actual pattern names detected with the system-detected patterns. Table 2 demonstrates that the model's actual patterns match the detected patterns. Table 2 provides a summary of the model's performance by emphasizing cases in which the detected patterns are accurate. It illustrates that the model was 100% correct in classifying the provided samples into the appropriate textile classes.

4. Conclusion

The results of the investigation show that the CNN-based Kalinga Textile Recognition model performs well, especially in terms of accuracy. The model exhibits a clear learning pattern, with decreasing loss and increasing accuracy, indicating its ability to recognize important features and patterns in the dataset. Additionally, the findings show high precision, recall, and F1-score across various classes, demonstrating the model's reliability in correctly identifying cases.

Table 2: Comparison of actual pattern name detected vs system detected pattern

Sample No.	Actual pattern name	Detected pattern name	Remarks (correct, incorrect)
1	Bilalikted	Bilalikted	Correct
2	Ilaglis	Ilaglis	Correct
3	Kayaw	Kayaw	Correct
4	Kilayaw	Kilayaw	Correct
5	Lilabey	Lilabey	Correct
6	Pilagpageyn	Pilagpageyn	Correct
7	Pilaslang	Pilaslang	Correct
8	Silaksakaw	Silaksakaw	Correct
9	Silambituwon	Silambituwon	Correct
10	Silugwid	Silugwid	Correct

However, the analysis of the confusion matrix highlights some limitations, as the model occasionally misclassifies cases, particularly among closely related classes. This is evident from the diagonal entries in the matrix. To improve the model's functionality and overall performance, further research and feature analysis are needed to address these misclassifications.

In conclusion, the CNN-based Kalinga Textile Recognition model shows promise in terms of accuracy and its ability to classify a wide range of classes successfully. Despite its achievements, the study underscores the importance of ongoing efforts to refine the model, reduce misclassifications, and explore additional improvements to ensure it can be used practically and reliably in real-world situations.

5. Recommendations

Future efforts and studies can focus on enhancing the CNN-based Kalinga Textile Recognition model by addressing its identified weaknesses. One way to improve the model is by thoroughly analyzing the misclassifications, particularly those involving closely related classes revealed by the confusion matrix. This could include experimenting with feature engineering techniques or optimizing the model architecture to better capture subtle differences between similar textile patterns.

Collaborating with textile experts and incorporating domain-specific knowledge can further enhance the model's understanding of textile nuances, leading to more accurate classifications. Additionally, using explainability techniques in the model's decision-making process can make it more transparent and reliable, especially for critical applications.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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