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Habesha cultural cloth classification using deep learning

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Habesha kemis, an Ethiopian attire traditionally donned by women belonging to the Habesha community, has undergone variations of designs over time. Initially, it comprised a lengthy dress with a fitted bodice and sleeves extending to the ankles. In the Amhara region, various ethnic groups such as Gojjam, Gondar, Shewa, Agew, and Wollo uphold their distinct cultural customs. While these Habesha garments may appear similar outwardly, their embroidered motifs exhibit unique patterns, shapes, and hues, symbolizing the rich cultural legacy of Gojjam, Gondar, Shewa, Agew, and Wollo. The study aimed to identify the most appropriate model for recognizing and classifying the quality of Habesha kemis embroidery design. Digital image processing methods and CNN models incorporating VGG16, VGG19, and ResNet50v2 classifiers were used. Following the gathering of datasets, image preprocessing and segmentation were employed to enhance the model's performance. In segmentation, we used canny edge detection, local binary pattern, and dilation with contour detection for segmenting and automatically cropping each habesha kemis. After applying the segmentation process, the individual habesha kemis and foreign matters are placed in a folder based on their corresponding categories. This resulted in 320 images before augmenting for each class amount representative. The performance of VGG16, VGG19, and ResNet50v2 for Agew, Gojjam, Gonder, Shewa, and Wollo was evaluated. This process resulted in an image size of 224 × 224 in the CNN model with a VGG16 architecture and a SoftMax classifier of course we try also 64 × 64 and 128 × 128. Augmentation techniques were applied to increase the dataset size from 1600 to 3,270. Finally, the model was evaluated and achieved an accuracy of 95.72% in test data and 99.62% in training data compared to the VGG19 and ResNet50v2 models.

Keywords Ethiopian cultural cloth, Habesha kemis, Embroidery design, Shemma

The Ethiopian Habesha dress comprises various garments, with the Kemis being the most iconic. It is a long, flowing white cotton dress known for its loose-fitting style, wide sleeves, and rounded neckline. Worn by both men and women, the Kemis hold a central position in the Habesha dress tradition, showcasing the simplicity, elegance, and grace of Ethiopian attire[1]. Another integral part of the Habesha dress is the Netela, a lightweight shawl crafted from versatile fabric. The Netela is often draped over the shoulders or around the waist, adding a touch of sophistication and practicality to the ensemble. Additionally, the gabi, a sizable rectangular cloak, is primarily worn by men. It is an outer garment during colder weather or special occasions, symbolizing formality, respect, and cultural significance. Recently, the Habesha cultural cloth has gained international acclaim and admiration. Its distinct beauty and cultural significance have captivated the attention of fashion designers, historians, and enthusiasts worldwide[2]. The elaborate patterns, vibrant hues, and exceptional craftsmanship have made their way onto global fashion runways and contemporary styles, bridging the gap between traditional and modern aesthetics. It allows us to recognize and value the diversity, artistry, and symbolism interwoven in these textiles. By delving into the complexities of Habesha cultural cloth, we can gain profound insights into the traditions, customs, and narratives of the Habesha people. This fosters a deep appreciation for their culture and facilitates cross-cultural exchanges and conversations. One of the most known and most common cultural cloths is made from cotton, which is called "Shemma." There are small and micro enterprises (SMEs) in Ethiopia that produce cultural clothes such as "Tibeb" or Habesha Kemis, which is called women's cultural dress, netela, Gabbi, and men's traditional clothes[3]. This traditional cloth is produced throughout the country in different SMEs based on the cultural identity of the people[2]. This research focused mainly on recognizing and classifying women's Habesha kemis cloths in different cultures, especially in the Amhara region, based on the embroidery design. In the Amhara region, people have their own cultural perspectives. People who live in Gojjam, Gondar, Shewa, Agew, and Wollo have different cultures. Women and men in this wear Habesha kemis for different festivals such as New Year, the finding of the True Cross, Crist mass, and Easter. To identify and categorize this traditional

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garment, a deep learning algorithm was employed[3]. Deep learning (DL) is utilized as a technique for learning representations by extracting a hierarchy of concepts from the available data. DL achieves this by utilizing neural network architectures, enabling the extraction of hierarchical features that are well-suited for modeling high-dimensional data. DL serves as a versatile learning algorithm capable of extracting hierarchical features to effectively represent the given dataset. As the network undergoes training to classify images into predefined categories, each layer acquires the ability to identify the essential features required for accurate classification. Deep learning (DL) employs multiple layers and sections within layers to represent more intricate functions[4,5]. These hierarchical layers employ specialized processing elements to generate both low-level and high-level features. This hierarchy enables control over the learning process, allowing DL to adapt to new problems and deliver superior performance compared to traditional methods. Lower-level layers specialize in recognizing basic features, while higher-level layers combine these low-level features to form more complex ones. Ultimately, the output layer classifies the image and produces the corresponding class label. DL offers the advantage of reducing the reliance on manual feature extraction algorithms, as the focus shifts towards training the network to learn these filters on its own. Recently, computer vision and machine learning algorithms have played an important role in garment texture design and processing of the colors and patterns of the clothes in many fashion productions. Therefore, to classify Habesha kemis embroidery designs, we used CNN for deep feature extraction and the Gabor filter algorithm. The primary objective of this study was to utilize computer vision techniques and various machine learning algorithms to categorize the Habesha kemis into different regional styles, such as Gondar, Gojjam, Shewa, Agew, and Wollo, based on their distinct embroidery designs. CNN is capable of automatically detecting significant features in an image without requiring human supervision[6]. These networks often consist of multiple convolutional and pooling layers, followed by a fully connected network. By employing this architecture, CNNs are capable of constructing a hierarchy of concepts, where more complex and abstract concepts are built upon simpler ones. The convolution and pooling layers are responsible for generating features, while the subsequent standard neural network learns the final classification function[7]. Deep learning makes it feasible to automate the process of differentiating designs from various locations, including Gondar, Gojjam, Shewa, and Wollo. By incorporating contemporary AI technologies, can improve cultural preservation, expedite production, and even promote these ancient designs internationally. Furthermore, deep learning provides consistency and scalability, making it possible to classify a huge number of designs effectively without the need for human labeling. This has major benefits for researchers, artists, and companies who want to use technology to innovate and expand globally without sacrificing authenticity. Finally, the structure of the remaining sections is shown as follows: Related works are revised in the section "Literature Review." Section "Proposed Model Architecture" presents the proposed method and algorithm usage. Section "Experiment and results" presents the experiments and discussion. Section "Conclusion and recommendation" concludes the paper and outlines future work.

Related works

According to the author (Kebadu, June 2020), Ethiopia is a country rich in diverse cultures, and one prominent cultural aspect is the traditional attire known as Habesha kemis. This clothing culture is particularly prevalent in the Amhara regional state and holds significant importance. Although the Habesha kemis may appear similar, it showcases distinct variations in terms of texture, shapes, and colors in its embroidery design. In this research study, the focus lies on classifying three specific types of Habesha kemis: Gojjam, Gondar, and Wollo. With a limited dataset consisting of 99 samples for each class, amounting to a total of 297 samples, the objective is to accurately classify these different types of Habesha kemis. To achieve this, a computer vision and machine learning approach are employed. During the image preprocessing stage, the collected images are resized to a standardized dimension of 224 × 224 to ensure consistency. Deep features are extracted using a conventional neural network (CNN), which aids in capturing intricate patterns and characteristics of the Habesha kemis. Additionally, a handcrafted Gabor filter algorithm is utilized to extract texture features from the images. To classify the Habesha kemis into their respective classes, an end-to-end CNN model and the Radial Basis Function (RBF) kernel function of the Support Vector Machine (SVM) are employed. The SVM classifier is trained and tested using different feature vectors, including Gabor feature extraction, CNN feature extraction, and combined feature vectors. The results indicate promising accuracy rates, with 93% accuracy achieved using Gabor feature extraction, 95% accuracy with CNN feature extraction, and 96% accuracy when combining the feature vectors. This research endeavors to contribute to the classification and understanding of Habesha kemis based on embroidery design. By leveraging computer vision techniques and machine learning algorithms, it opens up possibilities for automated recognition and categorization of these traditional clothing items.

The other researchers (Afewerk, Abiye Jember, 2021) developed an automated system for identifying different fabrics of Habesha Kemis cloth that possess similar colors. They have proposed a combined approach utilizing a convolutional neural network (CNN) and handcrafted texture descriptors. The system consists of three main components: preprocessing, feature extraction, and classification. For classification, the researchers have employed both CNN and Support Vector Machine (SVM) algorithms. The proposed model has been implemented using Keras with TensorFlow as the backend, programmed in Python 3.7. To validate the model, sample images were gathered from Habesha Kemis shops located in Gondar and Bahir Dar. The CNN model, when tested, achieved an impressive accuracy of 96%. The SVM model, on the other hand, employed different feature extraction techniques such as CNN, GLCM, LBP, and the Gabor filter as feature vectors. The individual SVM models achieved accuracy rates of 96%, 90%, 87%, and 93%, respectively. Furthermore, by combining the feature vectors of CNN and the Gabor filter, an accuracy of 99% was achieved. The proposed system offers a solution for automatically identifying different fabrics of Habesha Kemis cloth, despite their similar color patterns.

According to the author Bethlehem Nesibu (2017), this research mainly focuses on proposing an appropriate classification and coding system for Ethiopian cultural clothing. The current small and micro enterprises that produce cultural clothing are applying an informal grouping technique. Because of this, they spend too much time designing, setting prices, explaining the property of the product to customers, and retrieving already designed parts. To investigate this fact, samples of 111 small and micro enterprises that produce cultural clothes around the Gulele sub-city were studied. To conduct this study, a questionnaire, semi-structured interviews, and observation were employed. The information gathered by the questionnaire was analyzed by SPSS software to analyze the producers' perspectives on grouping similar parts. The codes will enhance better productivity by enabling the producers to estimate precise selling prices; with the symbols representing the characteristics of a certain product. They can also be used to document a specific design and retrieve it for later use. This act will enable the producers to eliminate duplication of effort by designing the same part more than once. DCLASS coding system is adopted and customized to classify and code parts of the cultural clothing. A database is developed to store the designs of these parts and use them for retrieval in the future.

Proposed system architecture

The components of the proposed system are preprocessing, data augmentation, segmentation, feature extraction, and classification (Fig. 1).

Image acquisition and data collection

To collect the Habesha kemis image, the Hadis Alemayehu Institute of Cultural Studies (in Debere Markos University), The Amhara regional state cultural office, and the east Gojjam Zone tourism and cultural office were contacted. a lot of research documents, and almost all cultural clothes found in the Amhara region, with their specifications; were collected from the Hadis Alemayehu Institute of Cultural Studies some of the pictures were

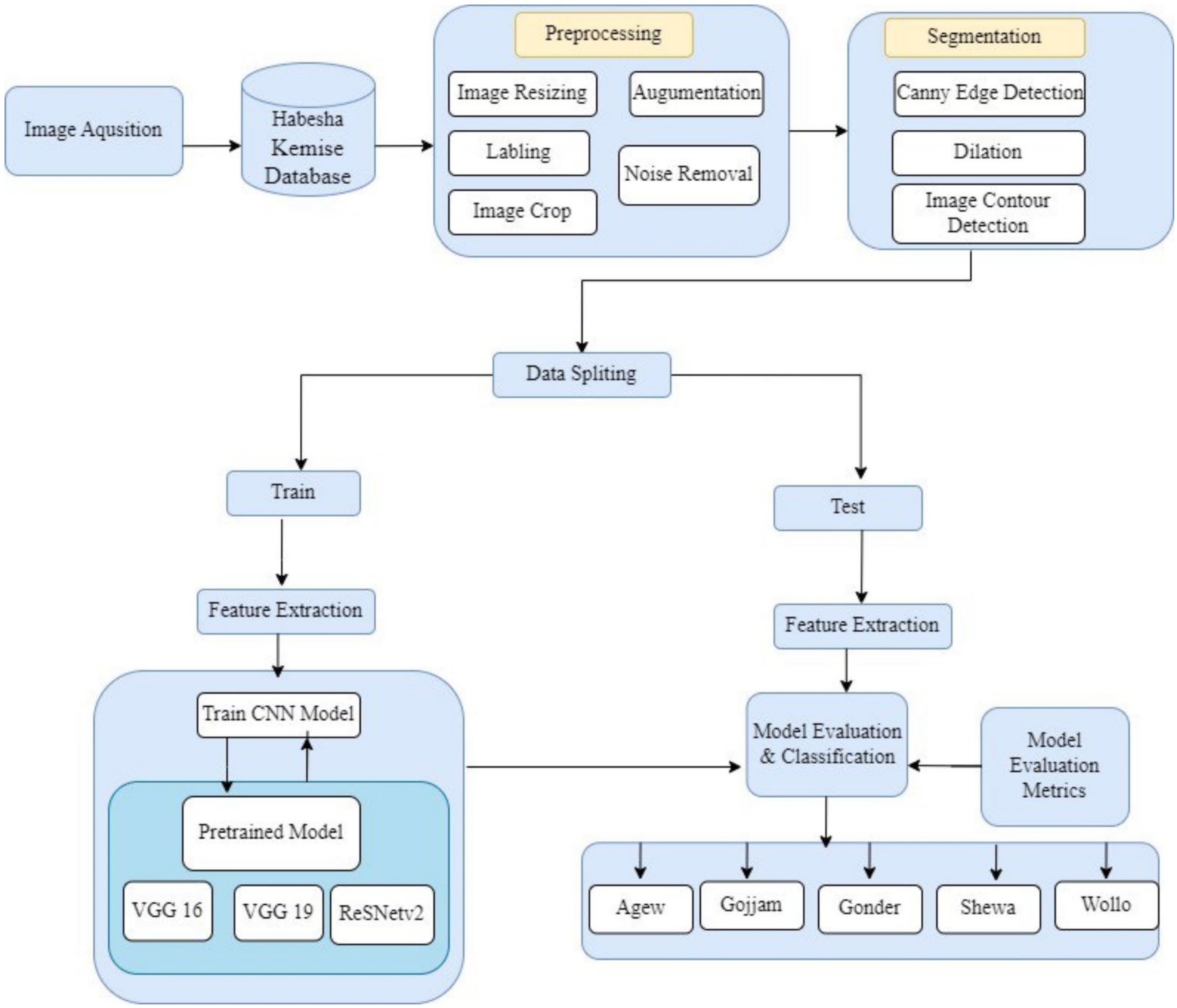

Fig. 1. Proposed research methodology architecture.

collected from The Amhara regional state cultural office., additional images were collected from East Gojjam tourism and cultural office. Most importantly, they helped in labeling all the data. As previously stated, we obtained the data from stores, government agencies, and other organizations, and they permitted us to use it in our article and any research use. Since we needed more pictures to fulfill our research dataset, we decided to capture the Habesha kemis directly from a different shop so, we used a Samsung Galaxy M30 mobile phone whose rear camera consists of a 13 MP + 5 MP (ultrawide) + 5 MP depth sensor lenses and 1080 × 2340 pixels resolution full HD camera to capture the Habesha Kemis Cloth images. In addition, we used different cultural videos based on East Gojjam tourism and cultural office suggestions, so that we can convert these videos into images. We used a VLC media player software to change the video to the image (https://www.filehorse.com/download-vlc-64/84057/). Additional Habesha kemis image is captured from Bahirdar Habesha kemis shop and Addis Ababa. Experts in East Gojjam Culture and Tourism Bureau and Hadis Alemayehu Institute of Cultural Studies helped us to classify the data correctly as Agew, Gojjam, Gondar, Shewa, and Wollo classes of the Habesha kemis. To label a dataset, we employ several techniques or guidelines. Some of these are for Shewa the white linen has been embroidered women on the cuffs, in the center, on the bottom, or all three. The white "netela," or scarf, is wrapped around the same fabric and design color as this, for Gonder features an elaborate embroidery design on the shoulder in addition to a broad ring of embroidery on the lower hem, but only on the back and it has embroidery on the sleeve, it appears to Gojjam and Gonder to be the same, but it isn't. Its shoulder features embroidery design is different, and the color combination of the front embroidery design, for Wollo front embroidery design is large and it has a sleeve design on the hand, Agew perceives Shewa and Gojjam as being similar, although their needlework styles and color schemes differ. They all paired with the white netela. In general, the color combination of their embroidery designs allows us to distinguish one from the other. We selected 320 images for each class and used 1600 Habesha kemis images before augmenting.

Figure 2 illustrates our attempt to display a selection of sample images from the dataset.

Preprocessing

Image preprocessing is necessary to guarantee compliance with the model's input specifications. Preprocessing can improve the speed of model inference and optimize model training time[8]. Reducing the size of input photos can drastically cut down on training time without sacrificing model performance when working with huge images[9]. As a result, the Ethiopian ethnic women's cloth embroidered design photographs undergo a variety of preprocessing procedures, including grayscale conversion, resizing, quality enhancement, cropping, and the application of other pertinent techniques[9].

Standardize images Because of a significant limitation in certain deep learning algorithms, such as CNN, we have harmonized the size of the Habesha kemis cloth images in our dataset. This suggests that before being sent to the learning system, photos need to be pre-processed and resized to have the same widths and heights. The algorithm used to process the dataset determines the image's size. Image resizing contributes to the common vision models' continuous performance improvement[10]. At the preprocessing phase, the image resize was changed to (224 × 224). In state-of-the-art models, the image size of (224 × 224) is taken as an input. Here, we experimented with several image sizes, including 64 × 64, 128 × 128, and 224 × 224. Therefore, it is practical to compare the network with state-of-the-art models using an image size of 224 by 224.

Fig. 2. Sample Images from the dataset.

Adjust image quality The process of modifying digital photos so that further image analysis may be done with the findings. In Habesha tribal textile photos, we have removed noise to make it easier to identify important elements. The noise reduction method smooths the entire image, leaving a region close to the contrast limit, to diminish or remove noise visible. In this paper, we removed noise from our samples by applying image smoothing. Image noise is a challenging process since it involves estimating the original image by reducing noise from a noisy source. For instance, you might want to eliminate disturbances from the image such as Gaussian noise, speckle noise, Poisson noise, and salt and pepper noise[11]. In this paper, we used the 5×5 Gaussian blur technique to try to eliminate or remove noise from an image sample. A Gaussian filter was used by applying an image to the function cv2.GaussianBlur, using kernel sizes of 5×5.

Contrast enhancement The most widely accepted method for improving image quality is histogram equalization. It enhances the overall look of photographs without erasing any important details. While histogram equalization usually yields better results, after the procedure is finished, some kinds of photos may occasionally show hidden noise. Histogram equalization, which makes use of cumulative distributive equalization, can produce very good results, especially when it comes to highlighting interesting features or boosting picture detail features to make better image modifications[12]. In this method, histogram equalization improves contrast in areas of an image with lower contrast. Adaptive Histogram Equalization (ADE) and contrasted limited adaptive histogram equalization (CLAHE) are the two advanced histogram equalization methods. This thesis addressed its contrast over-amplification issue by using CLAHE rather than AHE. A technique called CLAHE leverages local contrast enhancement to get beyond the limitations of global techniques. The contrast of the photos of the Habesh Kemis embroidery design has been enhanced using CLAHE[13]. Typical AHE is not the same as CLAHE due to its contrast limitation. To solve this problem of noise amplification, the CLAHE included a clipping cutoff. The CLAHE limits the amplification by clipping the histogram to a predetermined value before computing the cumulative distribution function. An input original image is divided into non-overlapping contextual components called sub-images, tiles, or blocks using the CLAHE approach. The two CLAHE parameters that regulate image quality are block size and clip limit. Every area of the context of the Habesh ethnic fabric image was subjected to histogram equalization using the CLAHE technique. The original histogram is cropped, and the clipped pixels are redistributed across each gray level. The intensity of each pixel in the redistributed histogram is restricted to a specified maximum, unlike the standard histogram[14]. The level of pixel strength values in the context region histogram is the pixel output value in CLAHE. The true histogram is dispersed throughout all the intensities within the recorded image range, whereas the histogram concentrates on the clipped pixels at a specific height. We were able to generate better Habesh Kemis embroidery design photos after applying the CLAHE approach. By generating a histogram equalization mapping for each pixel, the improved image was produced. Enhancing contrast brings out variations in image brightness[9].

Data augmentation

Data augmentation is an effective technique that can be used to improve overall performance, reduce overfitting, help models generalize to new data more effectively, and increase the diversity of training datasets. It can multiply the amount of training data that is accessible without requiring additional manual labor, making it a crucial technique in situations where obtaining big labeled datasets is challenging or costly[15]. Image augmentation comes in many forms; here are some of the most common: Vertical shift, horizontal shift, vertical flip, horizontal flip, rotation, brightness adjustment, and zoom in/out. Therefore, this paper applied data augmentation techniques on the Habesh Kemis cloth image dataset to increase the number of relevant images in our dataset. Image augmentation is applied to images to create different identical content to show the model for different training examples. This procedure aids in the resolution of overfitting issues and improves the model's capacity to generalize during training. In general, data augmentation using Keras can be used to artificially increase the size of a dataset and improve the robustness of a machine-learning model. In this case, we include Vertical shift, horizontal shift, vertical flip, horizontal flip, and rotation. We also specify that any empty pixels should be filled with the nearest pixel value[16,17]. You can see the detailed description in Table 1 below.

Segmentation

Image segmentation is a fundamental task in computer vision that involves partitioning an image into multiple segments or regions based on certain characteristics such as color, intensity, texture, or motion. The goal of image segmentation is to simplify the representation of an image by grouping pixels or regions that share similar properties, making it easier to analyze and extract meaningful information from the image. The ultimate goal is to obtain segmented regions that enable efficient analysis and interpretation of the image data[18]. These points

Augmentation technique	Purpose	Resulting images per class
Rotation	Simulates different garment orientations	320
Horizontal Flip	Mimics real-world variations	320
Vertical flip	Mimics real-world variations	320
Brightness Adjustment	Adapts to different lighting conditions	320
Zoom-in/out	Simulates different viewing distances	320
Total augmented per class	–	654
Total dataset after augmentation	–	3,270

Table 1. Augmentation technique.

Fig. 3. Sample canny edge detection from the dataset.

Fig. 4. Sample detecting contour from the dataset.

where the brightness of the image varies are called the edges (or borders) of the image. This is a technique widely used in the processing of digital images, such as model recognition, image morphology, and resource extraction. Edge detection allows users to observe the functionality of an image for a significant gray-level change[19].

1. ***Canny Edge Detection***: In this research, canny edge detection is used for detecting the shape or boundary of each embroidery. In the canny edge detection algorithm, first, the image should also be converted into gray-scale images, and this image should be free from noise by using a Gaussian blur filtering algorithm. Then, the Canny edge detection function uses blur images as a parameter and detects all the shapes of each Habesha kemis image, as shown in Fig. 3[20].
2. ***Dilation***: Dilation involves adding pixels to the object boundaries in an image. Then, after dilating the Habesh Kemis embroidery design images, the remaining task is detecting the position of each kernel by using a contour detection algorithm[21].
3. ***Contours Detection***: In image processing, a contour is a curve that joins points of equal intensity, brightness, or color in an image. Contours can be defined as the boundaries of an object in an image with continuous color or intensity. Contour detection is an essential step in many image-processing applications, such as object detection, recognition, and segmentation as shown in Fig. 4[18].

Classification

The final task of this work is classification. Various methods were employed in the classification process. This documentation uses the SoftMax activation function-equipped VGG16, VGG19, and ResNet50V2 classifiers. We selected these traditional learning models because they are well-liked and currently have excellent ratings for both feature extraction and classification[12]. Using the knowledge from the learning model—which is built via the training and testing phases classification is carried out. Throughout the training phase, the training dataset is used. We classify every image (in the testing dataset) into a particular or predetermined class (Agew, Gojjam, Gonder, Shewa, and Wollo) based on the knowledge from the learning model. The classification was finished once the distinctive traits were understood. Feature learning involves multiple layers layered on top of one another. This section describes each phase's operation used to learn features and classify the data into predetermined groups (Agew, Gojjam, Gonder, Shewa, and Wollo). We employed a classification model, dividing the data into pre-established groups[23]. Image Segmentation is performed to isolate the embroidery motifs from the background. Because this helps the model focus on the embroidered patterns rather than background noise. If the segmentation effectively isolates the embroidery, the entire segmented image is fed into ResNet50v2, VGG16, and VGG19. Contour Detection & Dilation of the segmented embroidery regions are detected and dilated to enhance the pattern boundaries. This step ensures that fine-grained textures and shapes are well-defined before passing the image to CNNs.

Experimental setup and result analysis

Experimental setup

The data is partitioned into training and testing datasets. We used 80% of the data for training the model, and 20% of the data was allotted for testing. Out of the 80% training dataset, 20% were used for validation during training. We alternatively tried 70% for training and 30% for testing and obtained better results than 80/20. System performance is strongly dependent on and has a good relationship with network parameter selection. Since there are many hyperparameters to test in each phase, we choose the best values for each hyperparameter of the network architecture of the model. In this proposed system, different parameters were tested, and the model with the smallest loss or error rate was selected. The goal of testing different hyperparameters is to decrease the percentage of loss function while improving the performance values for our evaluation metrics.

Models

Three distinct neural network models are compared in this model's examination for the classification of images including the Habesha kemis embroidered design. Feature flatten, a fully connected layer, dropout, and a Softmax classifier were added to the models. We reached objectives with better accuracy when we selected and employed this CNN. We discovered a good representation of our test goals utilizing metrics when assessing network performance. The models indicated above were trained and the batches were modified to the same formats (batch size, input scale) before the input photos were passed through deep neural networks, which operate as feature extractors. In addition, our neural network-based classifiers use the Adam optimizer during training to minimize the categorical cross-entropy by backpropagating the error. Different sets of hyper-parameters seen during training were then used to validate the models. A vector of probabilities indicating whether or not an input image belongs to one of the classes is produced by the Softmax classifier. The class with the highest value is the last one, and its position is then mapped back to a class. The model is trained with a beginning or initial learning rate of 0.001 (1e–3), 30 epochs, and batch sizes of 32 and 64. The dataset is divided into training and testing subsets, whereby the model is trained on the training dataset and its performance is evaluated on the test dataset.

Results

The proposed model underwent multiple training iterations using the VGG16 CNN model with a dataset of images resized to 224 × 224. Finally, as shown in, Figs. 5, 6, 7 and 8, and Table 2 we compared the outcome.

Discussions

This paper provides a detailed description of the experimental results of the suggested model for the design and classification of Habesha kemis embroidery. A brief explanation is given of the suggested model's implementation and the dataset that was used. The three deep CNN models that we have created are ResNet50v2, VGG16, and VGG19. The same optimizer, learning rate, and epoch were used to train these models. For each model, we have defined the experimental result. We went into great depth on the accuracy, loss curve, confusion matrix, and classification report for each model. The results of the model evaluation are presented in Table 1. The models are trained using an equal image size. We experimented with several image sizes, including 64 × 64, 128 × 128, and 224 × 224; the latter yielded superior results. We utilized the normal image sizes (224 × 224) in these trained models. We have assessed our model's performance by contrasting it with the most advanced models available. Using two distinct batch sizes, we first demonstrated the models' performance. The models were trained using 32 and 64 different batch sizes. Our model's performance indicated a slight variation in test and training accuracy when the batch size was changed. The trained models in batch size 64 outperformed those in batch size 32, as can be shown in Table 1. Furthermore, models are compared according to their accuracy, loss, and parameter size. It is preferable to train the model rapidly on a small scale in terms of size. Consequently, VGG16 has improved the efficiency of the computing resources, particularly those that are utilized in memory. The VGG16 model has obtained greater accuracy for Habesha kemis image pattern recognition and classification based on the model's accuracy. The VGG16 model, trained in a batch size of 32, produced a testing accuracy of 92.97% and a training accuracy of 98.31% in the experiment. Furthermore, the VGG16 model trained in a 64-batch size had an accuracy of 99.62% during training and 95.72% during testing in the experiment. Because of its low validation loss value (12.46%) and training on batch size 64, the VGG16 model performs better when it comes to identifying Habesha kemis picture embroidery designs. As a result, our model—VGG16 in batch size 64—performs better than the others. The VGG16 model, in general, guaranteed the best outcome free from issues with overfitting or underfitting. Compared to VGG19 and ResNet50v2, the VGG16 model has a better classification accuracy. Consequently, it is simpler to discover fresh Habesha kemis image embroidery designs VGG16 model.

Conclusion

In this study, we delved into the categorization and recognition issues related to Habesha kemis embroidery design using deep neural networks. AI can revolutionize traditional textile design by automating the creation and analysis of intricate patterns, helping preserve and enhance the unique heritage of Habesha garments. AI-driven tools such as computer vision and machine learning can assist artisans in optimizing embroidery patterns, improving consistency, and ensuring precision. Through our research, we discovered that CNNs have emerged as a significant area of study in this field, facilitating the automated recognition and classification of Habesha kemis embroidery designs. CNNs have proven to be an effective and fast way to obtain automated and

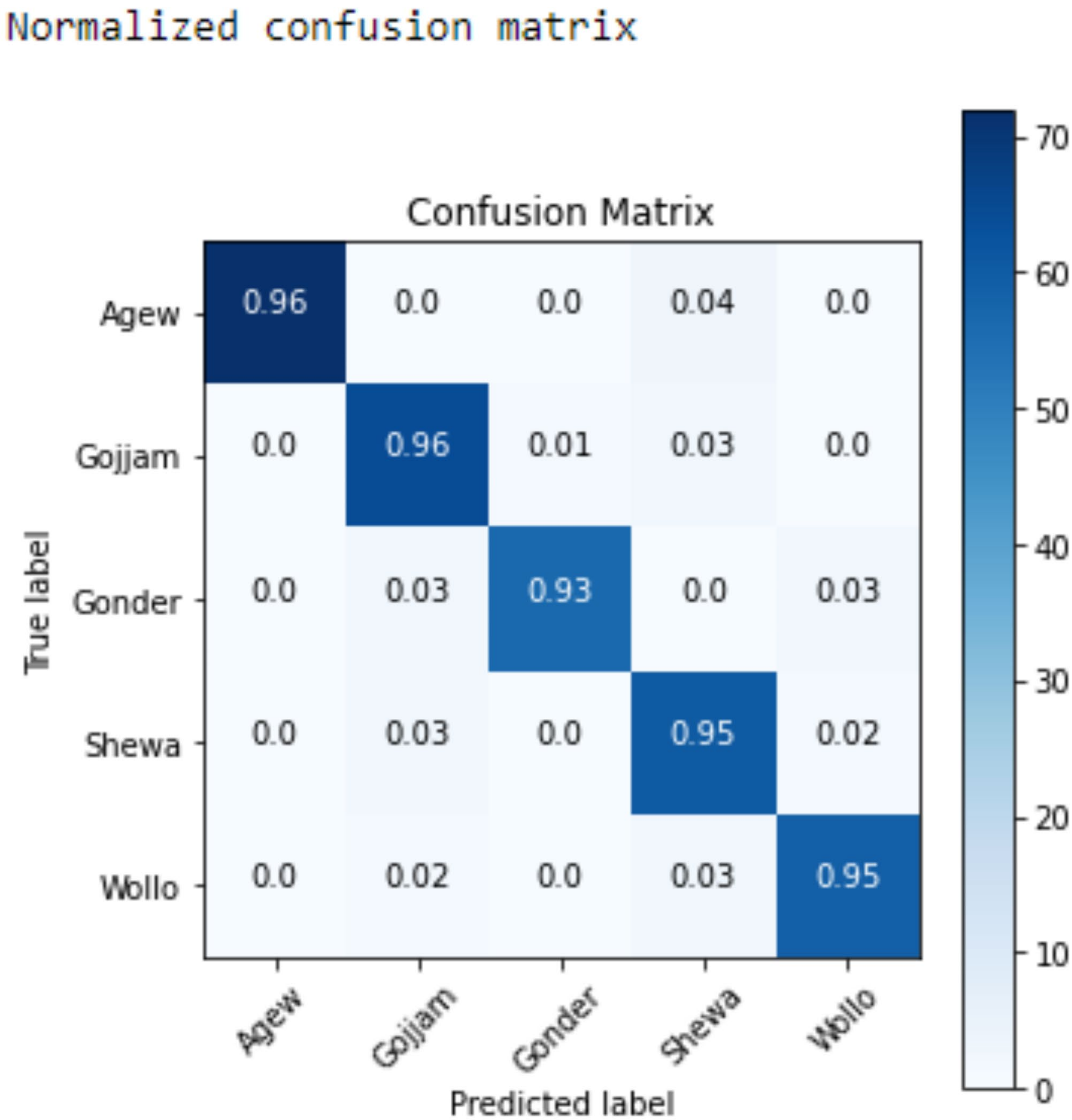

Fig. 5. Confusion matrix using VGG16.

efficient outcomes. After a thorough examination, we have identified Habesha kemis embroidery classification and pattern recognition, which are given tiny emphasis and are still unresolved problems. We have identified that different approaches, such as image processing and deep learning techniques, are highly applied for the pattern recognition and classification of images. A deep CNN model was developed for the detection and classification of Habesha kemis embroidery design and pattern using different Habesha cloths like Agew, Gojjam, Gonder, Shewa, and Wollo. Feature extraction by using canny edge detection, image contour, dilation, and local binary pattern can be easily applied to a wide range of image types, including grayscale, color, and texture images. In this work, we developed the Canny edge detection, local binary pattern, dilation, and counter-detection methods for the segmentation part. We used the deep learning CNN model VGG16 for feature extraction and classification purposes and SoftMax and ReLu as activation functions. As we discussed in the discussion part, the VGG16 was trained using RGB images with SoftMax activation functions and using different image sizes separately. In the first experiment, the VGG16 model was trained using a 32 × 32 batch size, and the number of epochs was 30. Of course, we tried different epoch sizes. Finally, we got better results in 30 epochs, and the image size was 224 × 224. The second experiment applied the same image size as the other experiment, which is 224 × 224 on batch size 64,

	precision	recall	f1-score	support
Agew	1.00	0.96	0.98	75
Gojjam	0.93	0.96	0.94	67
Gonder	0.98	0.93	0.96	60
Shewa	0.90	0.95	0.92	63
Wollo	0.95	0.95	0.95	62
accuracy			0.95	327
macro avg	0.95	0.95	0.95	327
weighted avg	0.95	0.95	0.95	327

Fig. 6. Classification report.

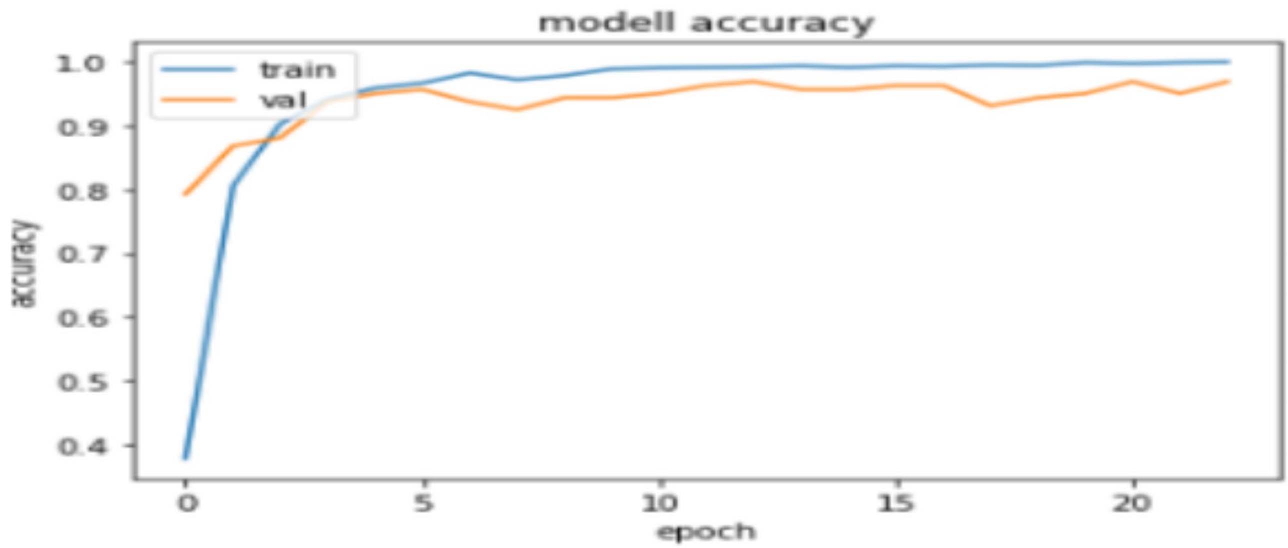

Fig. 7. Training and validation accuracy curve of VGG16.

and the result was 95.72% accuracy. Furthermore, we conducted a comparison of this model with two different CNN models, VGG19 and ResNet50v2. From those models, we have got 94.72% and 69% of the total accuracy of the model, respectively. 98 Therefore, we can conclude that our model is better than the VGG19 and ResNet50 models can be seen in Table 1, there is a model overfitting problem since the training and testing accuracy have a big difference between them. Whereas in experiments, the batch size of 64×64 is not an overfitting problem. Data augmentation refers to a set of techniques utilized to manipulate images during the data processing stage. These techniques are commonly employed alongside data pipelines to enhance model performance by reducing data bias and enhancing the model's ability to generalize to new data in real-world scenarios. Therefore, we can conclude that applying the augmentation process is important to remove the problem of overfitting. In addition to this, we also compare the size of Habesha kemis between 32×32 and 64×64 based on the results. There are no more outcome differences between the two kernel sizes, somewhat, 64×64 is better than 32×32, and also, when we see the real size of Habesha kemis, the 224×224 image size will be best matched. Of course, the execution time is high, but we get a better result on this image size. Habesha cloth symbolizes cultural pride, worn during celebrations, supporting local artisans and weavers. Economically, it boosts small businesses, promotes traditional craftsmanship, and contributes to Ethiopia's growing textile industry.

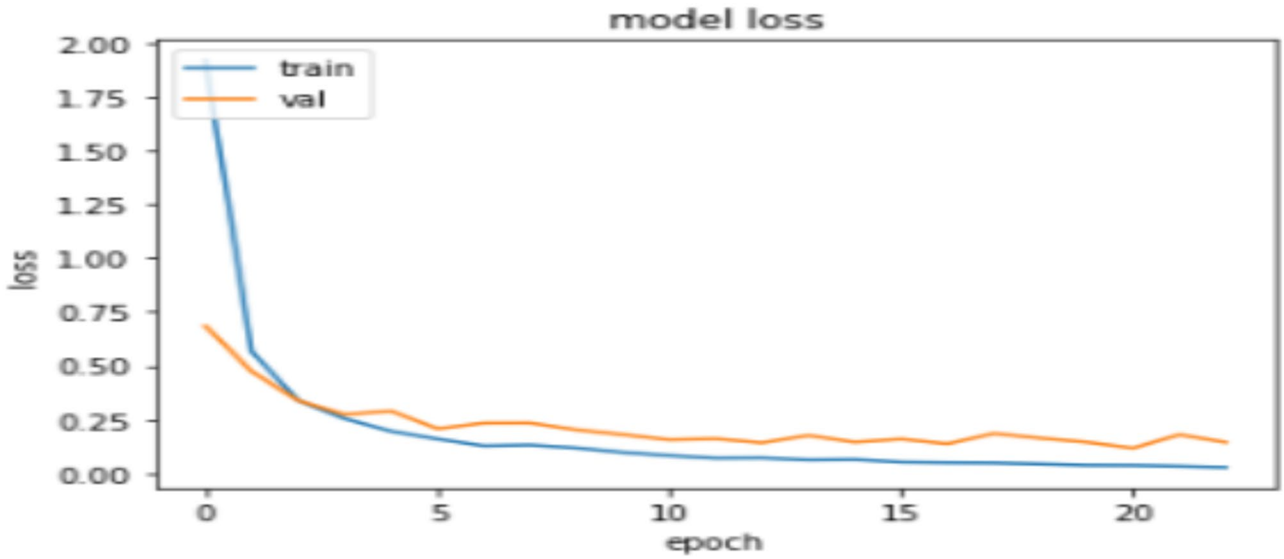

Fig. 8. Training and validation loss curve of VGG16.

Model	Epoch	Learning rate	Optimizer	Batch Size	Training accuracy (%)	Training loss (%)	Testing accuracy (%)	Testing loss (%)
VGG16	30	0.001	Adam	32	98.32	8.31	92.97	19.07
				64	99.62	2.94	95.72	13.92
VGG19	30	0.001	Adam	32	94.26	15.79	89.70	35.90
				64	97.24	10.94	92.05	21.49
ResNet50v2	30	0.001	Adam	32	56.61	84.46	58.10	68.11
				64	66.87	86.77	64.22	91.83

Table 2. Model result summary.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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References

1. Mekuriaw, K. Classification of Habesha Kemis Using embroidery design: a hybrid feature extraction approach. In *Msc thesis Submitt. to Bahir Dar Univ.* (2020).
2. Jember, A. *Automatic Identification of Ethiopian Habesha Kemis Cloth* (2021).
3. Part Family Formation of Ethiopian Cultural Clothing by using Group Technology Coding System Bethlehem Nesibu (Eng) Addis Ababa University 179–204 (2024).
4. Loke, K. S. Automatic recognition of clothes pattern and motifs empowering online fashion shopping. In *2017 IEEE Int. Conf. Consum. Electron.—Taiwan, ICCE-TW 2017, no. June 2017* 375–376 (2017). https://doi.org/10.1109/ICCE-China.2017.7991152.
5. Science, C. *Classification of Habesha Kemis Using Embroidery Design : a Hybrid Feature Extractio Approach* (2020).
6. Ye, J. C. Convolutional neural networks. *Math. Ind.* **37**, 113–134. https://doi.org/10.1007/978-981-16-6046-7_7 (2022).
7. Vijay, R. et al. Convenient clothing pattern and colour recognition for people with vision impairment. *IEEE Trans. Hum.-Mach. Syst.* **5**, 17–21 (2016).
8. Lakshmi Devi, P. & Subash, N. Digital Image Processing (R15a0426), vol. 2 (2019).
9. Son, N. H. Data cleaning and data preprocessing (2011). http://www.mimuw.edu.pl/~son/datamining/DM/4-preprocess.pdf.
10. Jerubbaal John, M. B., Luke, R. J. & Cognitive Impact of image size on accuracy and generalization of convolutional neural networks. *Int. J. Res. Anal. Rev.* **6**, 1 (2019).
11. Hambal, A. M., Pei, Z. & Libent Ishabailu, F. Image noise reduction and filtering techniques. *Int. J. Sci. Res.* **6**(3), 2319–7064. https://doi.org/10.21275/25031706 (2015).
12. Xi, H. & Chang, T. Image classification based on histogram intersection kernel. *J. Comput. Commun.* **03**(11), 158–163. https://doi.org/10.4236/jcc.2015.311025 (2015).
13. Zhou, W., Member, S., Gao, S., Zhang, L. & Lou, X. *Histogram of Oriented Gradients Feature Extraction from Raw Bayer Pattern Images, no. March* (2020). https://doi.org/10.1109/TCSII.2020.2980557.
14. Ma, J., Fan, X., Yang, S. X., Zhang, X. & Zhu, X. In *CContrast Limited Adaptive Histogram Equalization Based Fusion for Underwater Image Enhancement," no. March* 1–27 (2017).https://doi.org/10.20944/preprints201703.0086.v1.

15. Gavrilov, A. D., Jordache, A., Vasdani, M. & Deng, J. Preventing model overfitting and underfitting in convolutional neural networks. *Int. J. Softw. Sci. Comput. Intell.* **10**(4), 19–28. https://doi.org/10.4018/ijssci.2018100102 (2019).
16. Guyon, X. & Yao, J. On the underfitting and overfitting sets of models chosen by order selection criteria. *Comput. Intell. Neurosci.* **249**, 221–249 (1999).
17. Perez, L. & Wang, J. The effectiveness of data augmentation in image classification using deep learning (2017). http://arxiv.org/abs/1712.04621.
18. Arbel, P., Maire, M., Fowlkes, C. & Malik, J. In Contour Detection and Hierarchical Image Segmentation 1–20 (2022).
19. Khan, S., Kharade, R. & Lavange, V. In Segmentation in Digital Image Processing 1–3 (2019).
20. Abdulateef, S. & Salman, M. A comprehensive review of image segmentation techniques. *Iraqi J. Electr. Electron. Eng.* **17**(2), 166–175. https://doi.org/10.37917/ijeee.17.2.18 (2021).
21. Chaitra, G. N. & Khare, N. Feature extraction of clothing texture patterns for classification. In *Recent Emerg. Trends Comput. Comput. Sci. RETCOMP 2015, no. March* 6–9 (2015). https://doi.org/10.1109/RETCOMP.2015.7090796.
22. Salau, A. O. & Jain, S. Feature extraction: a survey of the types, techniques, applications. In *2019 Int. Conf. Signal Process. Commun. ICSC 2019, no. February 2020* 158–164 (2019). https://doi.org/10.1109/ICSC45622.2019.8938371.
23. Zhou, L., Li, Q., Huo, G. & Zhou, Y. Image classification using biomimetic pattern recognition with convolutional neural networks features. *Comput. Intell. Neurosci.* **2017**, 3792805. https://doi.org/10.1155/2017/3792805 (2017).

Author contributions

Problem identification and designed the analysis (Anteneh Demelash and Eshete Derb); Collected the data (Anteneh Demelash); Model Implementation (Anteneh Demelash; Performed the result analysis (Anteneh Demelash, Eshete Derb); Wrote the paper (Anteneh Demelash); Revised the paper (All authors).

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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