Classification of Saudi Traditional Costumes using Deep Learning Technique

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Abstract:
This study aimed to develop a system for classifying traditional clothing from the Kingdom of Saudi Arabia using convolutional neural networks. A dataset of 339 images across 3 categories was collected and preprocessed, including normalization, cropping, and blurring to enhance image quality.
The proposed system accomplished classification through a two-step process: Dataset collection utilizing Artificial intelligence (AI) techniques to gather 339 labeled images of clothing from Saudi Arabia which served as the training foundation, and classification using the Inception v3 CNN model with transfer learning.
Testing is achieved with an overall accuracy of 84.85% based on a confusion matrix, demonstrating the model's ability to correctly classify traditional clothing. Weighted Euclidean distance matching was also implemented to retrieve the top 5 similarity matches for query images.
A graphical user interface allows practical implementation and end-user clothing classification. The promising results indicate deep learning is viable for this application. However, limitations include the small dataset size. Future work involves collecting a larger, more diverse set of traditional Saudi clothing images to further improve classification performance.

Keywords:
Traditional Clothing, Saudi customs, Deep Learning, Inception v3 CNN model.

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1. Introduction:
In recent years, there has been a growing trend toward the use of technology in all aspects of life, including education, healthcare, business, entertainment, and social interaction. This trend is being driven by several factors, including the increasing availability and affordability of technology, the rise of the digital economy, and the need for greater efficiency and productivity in a rapidly changing world. As a result, technology has become an integral part of modern life, with its impact felt across societies and economies around the world (Schindler et al., 2021).
The world is now witnessing what is known as the fourth industrial revolution, which is led by big data technologies, and it has emerged as a result of technological development and the shift to the world of automation (, 2022). The fourth industrial revolution, also known as Industry 4.0, is characterized by the integration of advanced technologies such as AI, machine learning, and the Internet of Things (IoT) to create smart factories and processes. One of the key drivers of this revolution is big data technologies, which enable the collection, processing, and analysis of vast amounts of data generated by machines and devices (Shrouf et al., 2014; Bennett, 2020).
Big data technologies have become a crucial enabler of the fourth industrial revolution, facilitating the collection, processing, and analysis of large and complex datasets.
By leveraging big data technologies, businesses can gain valuable insights into their operations, identify areas for improvement, and make data-driven decisions to optimize their processes (Sestino et al., 2020). For instance, in the manufacturing sector, big data technologies can be used to monitor and analyze production processes in real time, identify anomalies, and predict equipment failures before they occur. This can help businesses reduce downtime, improve productivity, and enhance product quality (Lattanzi et al., 2021). In addition, big data technologies can be used to develop personalized products and services tailored to individual customer needs. By analyzing customer data, businesses can gain insights into customer preferences and behavior, enabling them to develop more targeted marketing campaigns and product offerings (Haleem et al., 2022).
Saudi Arabia has not been lagging behind. The Saudi government has always promoted AI. Crown Prince Mohammed bin Salman has made clear in his statement during his participation in the G20 summit in Japan that "we live in a time of scientific innovations, unprecedented technologies, and unlimited growth prospects. These new technologies, such as AI and the Internet of Things, if used optimally, can spare the world many harms

and bring the world many huge benefits (Saudigazette, 2019).
Now Saudi Arabia has witnessed a growing trend towards the use of technology in all aspects of life, including education, healthcare, business, entertainment, and social interaction. The trend toward the use of technology is also reflected in the government's efforts to promote digital transformation and modernize the economy (Justinia, 2022), (Konagala, 2022).
The Saudi Vision 2030 plan, which aims to diversify the economy and reduce the country's reliance on oil, includes several initiatives to promote the use of technology in various sectors, including healthcare, education, and finance (Saudi Vision 2030, n.d.). The government has launched several initiatives to support AI development and adoption, including the establishment of the Saudi Data and AI Authority (SDAIA) in 2019 (SDAIA, n.d). The SDAIA is responsible for developing and implementing national strategies for data and AI, promoting innovation and collaboration among stakeholders, and ensuring the ethical and responsible use of AI. The authority has launched several initiatives, including the National Strategy for Data and AI, which aims to position Saudi Arabia as a global leader in AI by 2030 (Sharma, 2021).
In addition to the government's efforts, the private sector has also been actively investing in AI technology and solutions. Saudi Aramco, the world's largest oil company, has launched an AI center to develop advanced analytics and machine learning capabilities for the oil and gas industry (Aramco, n.d.). The Saudi Telecom Company has also invested in AI technology to enhance its customer service and operations (Zawya, 2022).
The massive amount of data being produced, stored, and made available from various sources has become a significant asset for any knowledge-based society, having a profound impact on economic and social development if used optimally (Salma, 2022).
Classifying traditional clothing using AI can contribute to economic and social development in several ways. It can preserve the cultural heritage and ensure that future generations can appreciate and understand the significance of these garments. Additionally, by classifying traditional clothing, designers can gain insights into the design, style, and symbolism of these garments and use them as inspiration for creating new designs (Pantanella, 2022). Traditional clothing can be sold online, and accurate classification can help to improve the search and recommendation systems used in e-commerce platforms (Chakraborty et al., 2021). Traditional clothing can provide valuable insights into the social, economic, and cultural aspects of different societies, and by classifying traditional clothing, anthropologists can gain a better understanding of the symbolism, history, and cultural significance of these garments (europarl, n.d.). Finally, traditional clothing can be an attraction for tourists (Aldabbagh, 2019), and accurate classification can help to promote cultural tourism and raise awareness about the cultural heritage of different societies.
Therefore, this paper will focus on employing AI systems to preserve the cultural heritage and boost the fashion industry.
The main objective of this research is to prepare a dataset for traditional clothing in the Kingdom of Saudi Arabia using AI concepts.
This can contribute to cultural heritage preservation by providing an automated system for identifying and classifying different types of traditional costumes in Saudi Arabia. This can also help in preserving the culture and history by enabling the accurate identification and classification of traditional costumes, the research can also have an impact on the fashion industry, as it can help designers and manufacturers identify different styles and trends in traditional clothing. By leveraging deep learning methods, the study can provide insights into the patterns and characteristics of traditional costumes, which can inform the creation of new designs and products.
To do so, a deep learning model is developed to accurately classify different types of traditional costumes based on their design, color, and fabric.

2. Research Statement:

Fashion has been a crucial aspect of our daily routines and holds significance in society (Vijayaraj et al., 2022). In the Kingdom of Saudi Arabia, the clothing heritage is diverse, representing various styles and customs that showcase the history of the land and the heritage of our ancestors. Therefore, it is essential to preserve this heritage (Al-Bassam and Fadda, 2002). Numerous studies have been conducted to preserve cultural heritage and prevent its loss over time. For instance, (Fida,1993) aimed to preserve the heritage of the Makkah Al-Mukarramah region by analyzing and studying the traditional clothing worn by women in the area. Al-Sahari (2018) has focused on linking technology to heritage preservation to raise awareness of traditional Saudi women's costumes by using a virtual museum to showcase them to a wider audience.
Through the literature review and attending courses on AI, the researcher realized the immense significance of integrating AI technologies in all fields of production. This is particularly crucial given the increasing demand and interest in AI's

potential applications. Interestingly, despite the growing interest in AI, there seems to be a significant gap in research in Arabic studies regarding the classification of clothing using AI. This highlights the need for further exploration and investigation into this area, as it could have significant implications for various industries.

Relating to the important responsibility of preserving cultural heritage, the researcher has proposed an innovative approach to collecting, classifying, researching, and analyzing traditional costumes using data science and deep learning techniques. This approach aims to narrow the gap between the past and present, by adopting modern methods and advanced technologies, with the ultimate goal of preserving cultural heritage. By leveraging data science and deep learning, this research will enable a comprehensive understanding of traditional costumes, their history, and their significance in various cultures.

Based on the above, the research problem has been summarized into the following key questions:

- Is it possible to use data science and deep learning techniques to effectively analyze and classify Saudi traditional costumes?
- What are the most effective methods for preparing a comprehensive dataset of traditional clothing in Saudi Arabia using AI concepts?

II. Review of related literature

Several studies have attempted to classify articles of clothing using deep learning techniques. Zhou et al., (2022) proposed a clothing classification method based on a parallel convolutional neural network (PCNN) combined with an optimized random vector functional link (RVFL). The method uses the PCNN model to extract features of clothing images. The experimental results show that on the Fashion-Mnist dataset, the accuracy of the algorithm in this study reaches 92.93%.

Madulid & Mayol (2019) created a clothing classification tool with the use of convolutional neural networks. A method for creating an automated clothing classifier was presented, trained from 5600 clothing images in 7 classes using the Inception architecture. The trained model obtained an estimated accuracy of 95%. The model identified different clothing categories with an accuracy of 96.2% in coherence with the estimated accuracy result. It also had a recall of 0.981 and a precision of 1.

Nawaz et al., (2018) used deep learning models to classify different types of Bangladeshi traditional clothing. The research proposed an approach that can automatically classify real-world pictures of some traditional clothing worn in Bangladesh into predefined classes using CNNs. Clothing images from several online stores were collected and labeled accordingly. The CNN model was based on the Google Inception model. For comparison purposes, several architectures of CNN and some variations were tried to see how the model performs against them. The model was tested with three different optimizers – SGD, Adam, and RmsProp. Among these optimizers, RmsProp performed the best. The final result shows the model could classify the images of the training and testing set with 92.05% and 89.22% accuracy respectively.

Wang et al., (2016) proposed a method, which combined Convolutional Neural Network (CNN) with Recurrent Neural Network to create a CNN-RNN framework, which can be used to classify multi-label images. Their method incorporated the convenience of the joint image-label embedding and label co-occurrence models by employing CNN and RNN to model the label co-occurrence dependency in a joint image/label embedding space. The experimental results they provide show that their method attained better performance than other state-of-the-art models .

Razavian et al., (2014) conducted some experiments regarding various recognition tasks. They accomplished this with codes that were accessible publicly and using the OverFeat network model. They trained the model to classify objects on OLSVRC13. They reported consistently better results when compared to highly tuned systems regarding visual classification. They attained such results by applying an SVM classifier to a size 4096 feature representation that was extracted from the network model. Their results suggested that, for visual recognition activity, features extracted from deep, CNN need to be the essential candidate.

1. Use of deep learning in the classification of traditional costumes

Traditional costumes are an important aspect of cultural heritage, and their classification can provide valuable insights into the history and culture of a region. Saudi Arabia is known for its rich cultural heritage, and traditional costumes play a significant role in the country's cultural identity. Each region in the Kingdom of Saudi Arabia has different tribes, and each tribe has its style, but only a few of those costumes were well known - the rest were forgotten due to the lack of proper documentation and tribal migration (Al-Bassam, 2012). Figure 1 illustrates an example of traditional costumes on display at an exhibition organized by the mansoojat foundation.

Figure 1. Traditional costumes are on display at an exhibition organized by the Mansoojat Foundation.

Classification and archiving of traditional costumes are important aspects of cultural and heritage preservation. In recent years, there has been an increased interest in classifying traditional costumes.

Classification of traditional clothing refers to the process of categorizing different types of traditional garments from various cultures based on their design, style, and cultural significance. It is an important research area that has the potential to contribute to cultural heritage preservation, fashion design, and e-commerce. The classification of traditional clothing can be achieved through various methods, including machine learning, image processing, and computer vision techniques (Ye, Q, 2023).

AI is a rapidly growing field of computer science that focuses on developing machines and algorithms that can perform tasks that typically require human-level intelligence, such as understanding natural language, recognizing images, and making decisions. Recent advances in AI have been driven by the development of deep learning, a subset of machine learning that uses neural networks with many layers to extract features from complex data. It has become one of the most rapidly growing and impactful areas of AI (AI) in recent years, with applications in a wide range of fields (Choudhary et al., 2022).

Deep learning has become a powerful tool for solving complex pattern recognition problems, including image classification. In recent years, researchers have applied deep learning techniques to classify traditional clothing from different cultures around the world (Taye, 2023).

2. Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that is commonly used for image recognition and classification tasks (Yamashita et al., 2018). CNNs are based on the structure of the human visual system and are designed to learn hierarchical representations of images (Lindsay, 2020). CNNs consist of multiple layers of artificial neurons that are arranged in a series of convolutional and pooling layers. In the convolutional layers, the neurons learn to detect local patterns or features in the input image, such as edges or textures. The pooling layers downs ample the feature maps generated by the convolutional layers, reducing the size of the representation while preserving the most salient features. CNNs have been used in various applications, including image recognition and classification tasks (Nirthika et al., 2022). CNNs are particularly well-suited for these applications because they can learn hierarchical representations of images and identify patterns in the data (Yamashita et al., 2018). The CNNs are a cutting-edge model architecture widely used for image classification tasks. They employ a sequence of filters to process the raw pixel data of an image, extracting and learning higher-level features that enable accurate classification.

3. Inception v3

Inception v3 is a convolutional neural network (CNN) model that has been widely used for image classification tasks. It was developed by researchers at Google and was trained on the ImageNet dataset, which consists of millions of labeled images from thousands of categories.

The Inception v3 model is an extension of the earlier Inception models, aiming to improve accuracy and efficiency in image recognition tasks. It incorporates several architectural advancements, including the use of "Inception modules" that allow for efficient computation by using multiple filter sizes within the same layer (Meena et al., 2023)

The Inception v3 model has achieved impressive results in various image classification benchmarks and competitions, demonstrating its effectiveness in recognizing objects and scenes within images. It has also been used as a starting point for transfer learning, where pre-trained Inception v3 models are fine-tuned on specific tasks with smaller datasets.

The Inception v3 model can be used for traditional clothing classification tasks, to classify images of traditional attire from different cultures or regions. By training the model on a dataset containing images of traditional clothing, it can learn to recognize and classify different types of traditional garments (Shah et al., 2023).

The Inception v3 model, developed by Google researchers, is a deep convolutional neural network specifically designed and validated using the ImageNet dataset, which serves as an academic benchmark for computer vision tasks. Figure 2 illustrates the standard architecture of Inception v3. The Inception model has been developed by many researchers over the years. The model is made up of building symmetric and asymmetric layers, convolutions, pooling, concatenations, dropouts, and fully connected layers.

In the Inception v3 model, the final layers serve as high-level detectors for entire objects. To incorporate the recognition of new classes, such as clothes, transfer learning was applied. This involved leveraging the knowledge gained from previous training sessions of the Inception layers and retraining the final layer specifically for the new classes. This approach allowed the model to expand its repertoire of knowledge without erasing the entire existing model.

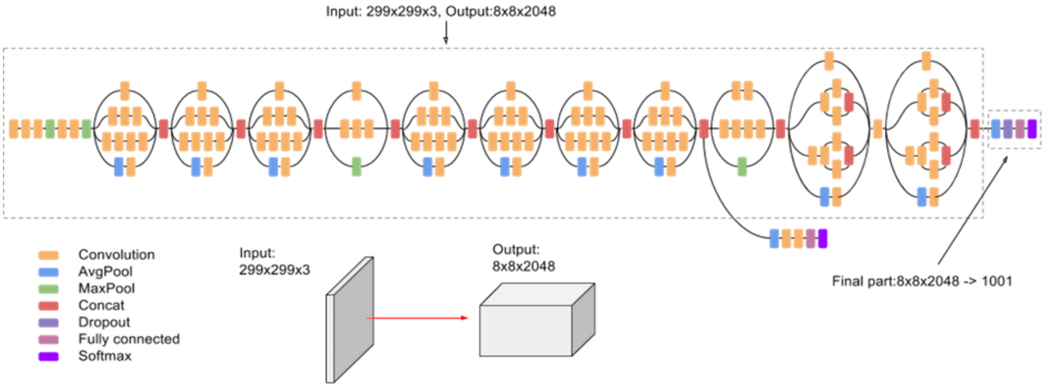

Figure 2. A high-level architecture of the Inception v3 model, to make it run efficiently on the cloud [https://cloud.google.com/tpu/docs/inception-v3-advanced].

MATLAB is used as an environment to build a scientific and engineering applications. Accordingly, a graphical user interface (GUI) can be created to build interactive applications with buttons, menus, sliders, plots, and other visual elements. The MATLAB provides a set of tools and functions specifically designed for such GUI. Additionally, MATLAB provides various functions and libraries for creating custom graphics, plotting data, and handling user inputs, which can be integrated into a GUI application (Mathworks. n.d.)

III. Methodology:

The proposed system consists of two fundamental steps. The first step involves the collection of a dataset for traditional clothing in the Kingdom of Saudi Arabia, utilizing AI techniques. This dataset serves as the foundation for the subsequent step, which involves the classification of traditional clothing using a Convolutional Neural Network (CNN). This classification process is a crucial component of the proposed system and can be further divided into two main phases: the training phase and the testing phase, as illustrated in Figure 3.

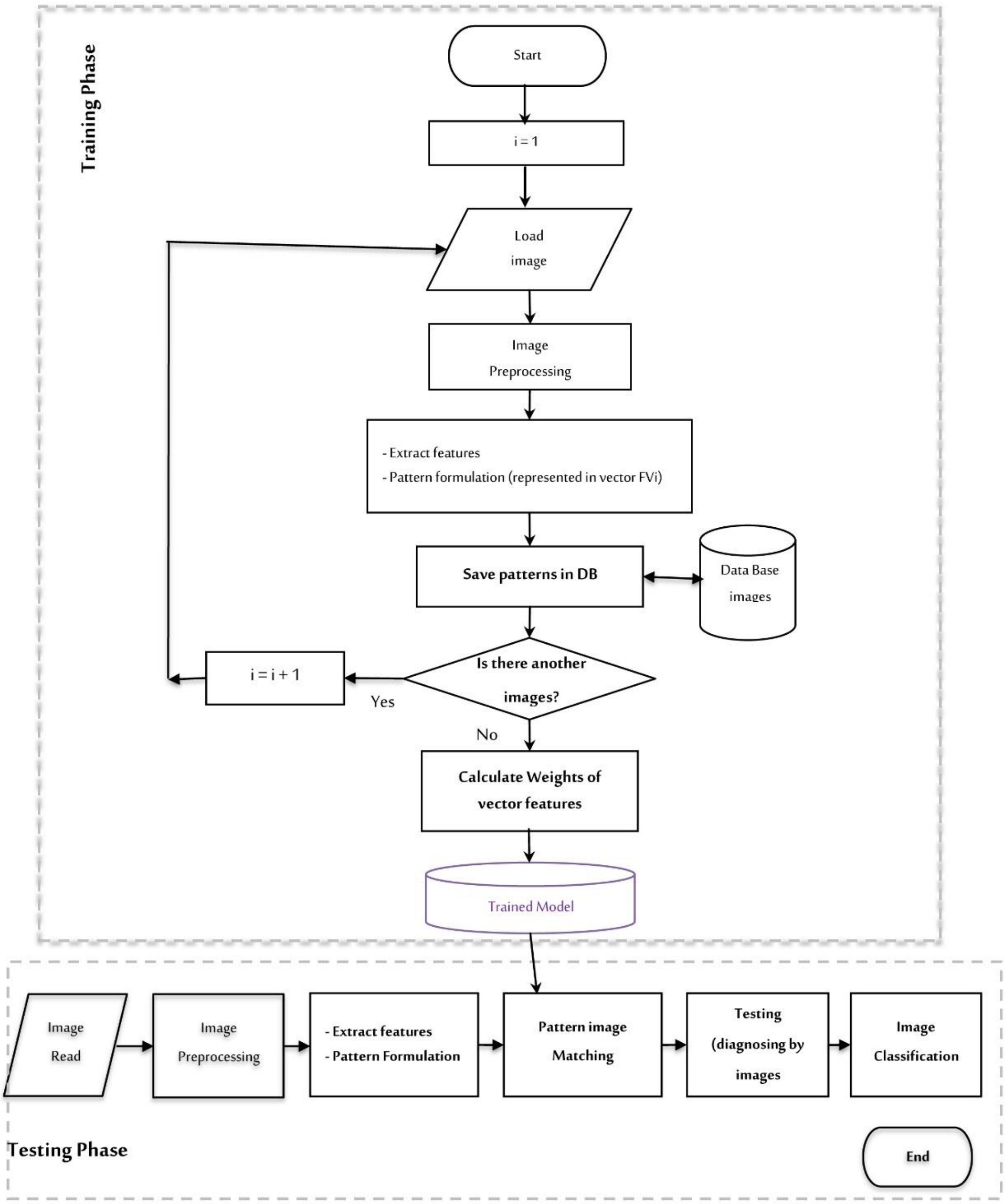

Figure 3. Flowchart for traditional clothing classification.

1. Dataset Preparation:

As part of the image preparation stage, several techniques were employed to enhance the images and remove any corruption. This was achieved by resizing the images to a standard size and applying image effects such as shear and horizontal flipping.

The dataset utilized for image classification comprised a total of 339 traditional clothing images. These images were obtained from generic search results and subsequently underwent a meticulous cleaning process (Nawaz et al., 2018).

To ensure accurate classification, the dataset was manually classified and labeled into distinct categories. In line with the Pareto principle, which suggests that 80% of the effects stem from 20% of the causes, the dataset was divided accordingly. Specifically, 80% of the data (319 images) were allocated for the training dataset, while the remaining 20% (80 images) were reserved for the evaluation set. The distribution of images across each category can be found in Table 1:

Table 1. List of Number of images used

Class Name	Training set	Testing set	Total
Makkah	114	28	142
Madinah	72	17	89
Taif	87	21	108
Total	273	66	339

2. Training Phase:

The training phase encompasses three key steps: image acquisition, image pre-processing, and image feature extraction. These steps are crucial for preparing the dataset and extracting meaningful features from the traditional clothing images. After collecting the images, they were categorized into three distinct classes. Table 2 provides a sample of traditional clothing images, showcasing the diversity and variety within each class.

Table 2. Samples of traditional clothing images.

No	Image	Class Name
1		Makkah
2		Madinah
3		Taif1

[(1)] Pphotos from the Fashion and Textile Department Museum, King Abdulaziz University, photographed by the researcher.

Once the bottlenecks, which represent the learned features, were computed, the training of the final layer commenced. The training process involved 8,000 training steps, twice the default number of 4,000 steps. In each step, random images from the training set were selected, and their corresponding bottlenecks were fed into the final layer to obtain predictions. These predictions were then compared against the actual labels to update the weights of the final layer. Throughout the training process, the reported accuracy improved, both in terms of training accuracy and validation accuracy. Higher values in these metrics indicated the model's progress in each training step.

Monitoring the training and validation accuracy was crucial in assessing the model's performance. If the training accuracy was high but the validation accuracy remained low, it suggested that the network was memorizing specific features in the training images that were not beneficial for generalization. The objective of training was to minimize the loss, so observing a downward trend in the loss, while disregarding short-term fluctuations, indicated effective learning.

The weighted Euclidean distance (WED) technique is used for the matching process, which passed from the following steps:

- Finding the WED among the QFV and all vectors FV_i.
- The formula of the WED measure is demonstrated as follows [2]:

$$d(v, v^k) = \sqrt{\sum_{i=1}^{n} p_i \, (v_i - v_i^k)^2} \qquad (1)$$

Where:

- v_i to balance the variations in the dynamic range.
- p_i the weight added to the component.
- k is the matched image index.

$$p_i = \frac{N}{\sum_{k-1}^{N} \left(v_i^k - \overline{v_i}\right)^2} \qquad (2)$$

N = the number of images in databases.

$$\overline{v_i} = \frac{\sum_{K=1}^{N} v_i^k}{N} \qquad (3)$$

- Sorting the WED values.
- The final decision is the one with smallest value of the WED.

IV. Experimental

1. Training

To train and test our Convolutional Neural Networks (CNNs), we utilized a Microsoft Surface Book 1 with an Intel(R) Core (TM) i5-6300U CPU running at 2.40 GHz (with a max turbo frequency of 2.50 GHz) and 8.00 GB of RAM. This hardware configuration proved sufficient for training our CNNs within a reasonable time frame.

The proposed model is implemented using C# in visual studio.net 2022, for Windows environment. Therefore, the GUI is implemented, and the MATLAB 2023 is used for Saudi traditional costumes classification. Figure 4 shows the main GUI of our proposed system.

Figure 4. The proposed system main GUI.

Figure 5 describes scenario of the running for the model traditional clothing images classification including query image and the nearest five images to the input query.

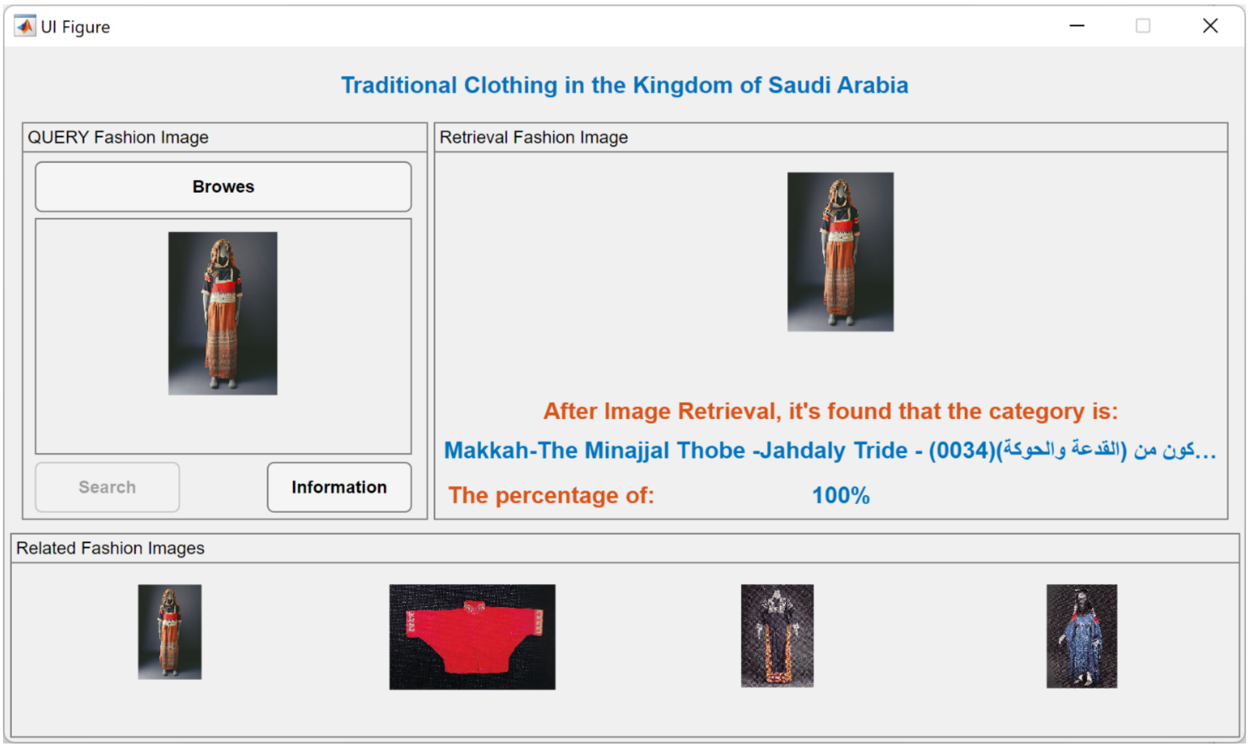

Figure 5. Testing and searching scenario for traditional clothing images classification system

2. Evaluation

For evaluating the performance of our system, we subjected the proposed system to a testing phase using a dataset consisting of 339 traditional clothing images. The proposed system successfully classified these images, and the resulting confusion matrix is depicted and displayed in Figure 6. The confusion matrix provides insights into the accuracy and misclassifications made by the system during the testing process.

This stage presented the class name, retrieved images related to query image, and the percentage of similarity between a query image and images in the data base.

Figure 6. Confusion matrix.

$$Accuracy = \frac{sum\ of\ correct\ classifications}{Total\ number\ of\ classifications} \times 100$$

(4)

$Accuracy =$ 84.85 %

Accuracy is the overall accuracy for traditional clothing classification.

$$Error\ Rate = 100 - Accuracy \qquad (5)$$

$$Error\ Rate = 15.15$$

Error Rate is the overall error rate for traditional clothing classification.

3. Comparison with previous studies

The dataset used in this study consists of 339 images across 3 clothing classes (Makkah, Madinah, Taif). In comparison, Madulid & Mayol (2019) used 5600 images in 7 classes, and Nawaz et al. (2018) collected clothing images from online stores for classification. The larger and more varied the dataset, the better the model's ability to generalize.

This study utilized transfer learning with the Inception v3 CNN model, leveraging features learned from the ImageNet dataset. Similarly, Madulid & Mayol (2019) used the Inception architecture, while Nawaz et al. (2018) used the Google Inception model. Each study adapted the pre-trained model to their specific classification task.

This study achieved an overall accuracy of 84.85% in classifying traditional clothing images. In comparison, Zhou et al. (2022) achieved an accuracy of 92.93% on the Fashion-Mnist dataset, and Nawaz et al. (2018) achieved 89.22% accuracy on their testing set. Madulid & Mayol (2019) reported an estimated accuracy of 95% on their trained model.

Different studies employed various techniques and approaches. For example, this study used weighted Euclidean distance (WED) for image matching and applied data augmentation through resizing and flipping. Madulid & Mayol (2019) focused on creating an automated clothing classifier, and Nawaz et al. (2018) compared different CNN architectures and optimizers. Wang et al. (2016) proposed a CNN-RNN framework for multi-label image classification, and Razavian et al. (2014) explored recognition tasks using the OverFeat network model.

V. Conclusion

The proposed system aims to classify traditional clothing from the Kingdom of Saudi Arabia using convolutional neural networks (CNNs). A dataset of 339 images across 3 clothing classes (Makkah, Madinah, Taif) was collected and preprocessed.

For the training phase, 80% of images (319) were used to train the Inception v3 CNN model using transfer learning. The final layer was retrained to recognize the new clothing classes while leveraging features learned from prior ImageNet training. Training accuracy and validation accuracy were monitored to prevent overfitting.

Testing was conducted on the remaining 20% of images (80). The confusion matrix shows the proposed system achieved an overall accuracy of 84.85% in classifying the traditional clothing images.

Some key techniques used include weighted Euclidean distance (WED) for image matching and data augmentation through resizing and flipping. A graphical user interface (GUI) was also developed to classify query images and display the top 5 matches.

In conclusion, the proposed CNN model leveraging transfer learning from Inception v3 achieved promising results for traditional clothing classification from Saudi Arabia, demonstrating the viability of deep learning approaches for this application. Further improvements could involve collecting a larger more varied dataset.

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