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EGYPTIAN ARTIFACTS' MATERIALS CLASSIFIER BASED ON LIGHTWEIGHT DEEP LEARNING ARCHITECTURES

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Abstract:
Artificial Intelligence (AI) plays a crucial role in cultural heritage by enabling the analysis, preservation, and restoration of artifacts and historical documents. Most of these applications may require to be used on devices with limited resources which leads to the need to use lightweight models. This study employs lightweight deep learning models, MobileNet V3 and ResNet-50, to classify Egyptian artifacts based on seven different materials. The models are trained on a dataset of 10.274 images. MobileNet achieves a training accuracy of 99.6% and a validation accuracy of 78.75%, while ResNet-50 achieves 96.62% and 83.23%, respectively. This research represents a novel contribution as previous studies have not specifically addressed the classification of materials in Egyptian artifacts. Such advancements highlight AI's potential in making cultural heritage more accessible and enhancing historical under-standing.

1. Introduction

Cultural heritage is about the things that were developed, survived, and passed throughout different generations and eras [1]. The tangible and intangible cultural heritage are considered the main descriptions of the existing cultural heritage [2]. The tangible forms include artistic items, artifacts, paintings, objects, statues, and buildings. At the same time, the intangible forms can be recognized as the practices, languages, expressions, values, traditions, and rituals [2, 3]. In other words, the tangible forms can be expressed as the remaining physical items while the intangible forms are perceivings acquired through oral expressions, storytelling, clothing, religious thoughts, and ceremonies [2]. Preserving and studying cultural heritage have a significant impact on civilization and technology by reviving the connection to certain values, beliefs, and concepts. Due to the rapid development of digital technologies, there has been an increasing opportunity of expanding the effect of technology over preserving the cultural heritage and making them more accessible [4, 5]. The tangible items or objects can be converted using technology to a digitalized form which expands their availability and preserves them from various factors like stealing and wearing out. However, only preservation is insufficient where the recognition task is a necessity to identify and demonstrate the historical part that tells the story and its relevance. Despite that the existing archaeologists, museums, and libraries all over the world play a key role in conserving and promoting the tangible cultural heritage, artificial intelligence (AI) initiatives got impressive attention recently [5-8]. The reason behind that is the desire to maximize recognition automation with less human interference and higher accuracies. In the field of machine learning, material recognition is considerably an active research topic. Materials can be recognized and classified according to color, texture, and transparency degree. Despite that these features seem to be easily recognizable, implementing and training an appropriate material classifier is challenging due to the different lighting conditions that can affect the proprieties mentioned earlier. A specific research gap is related to the classification of materials of Egyptian artifacts. This aspect is further underscored by the absence of any or minimal studies, indicating the importance of our research. This is why this study has been devised to help further improve the identification and conservation of Egyptian artifacts, with the help of highly advanced tech solutions such as AI. We hope that creating state-of-the-art material classifiers allows for more accurate and faster identification of artifacts, thus expanding the scope of cultural heritage preservation. Material culture is one of the main aspects regarding the objects of cultural heritage. Materials can reveal information about the era, location, usage, development, and consumption. Also, by identifying the material of the historical items, important interpretations can be done regarding anthropology, weather, and evolution [9]. Since the dawn of mankind, materials shaped civilization so that the ancient period of time has been defined by the predominantly used material, *i.e.*, Stone Age, Bronze Age, Iron Age, which shows the important impact of the materials [10]. Ancient Egypt is considered one of the world's first settlements where a wide range of materials were abundantly available. This helped the ancient Egyptians to master a variety of techniques for material handling. Three different cultures prospered during the Predynastic period in Egypt: the Fayum, the Badarian, and the Naqada cultures as shown in fig. (1).

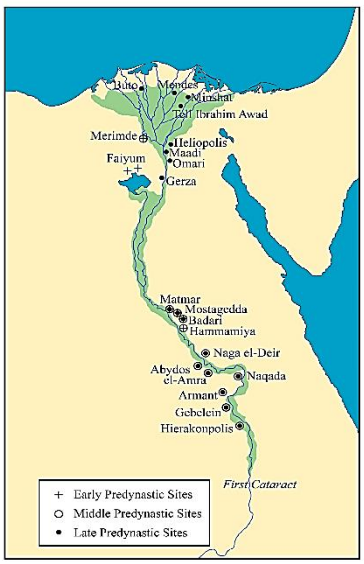


Figure (1) map of predynastic sites in Egypt [11].

Each demonstrated significant advancements in material handling to support settlement. The Fayum culture (9000-4400 BCE) flourished during the Palaeolithic age as early Egyptians settled near Fayum Lake, utilizing abundant water resources for pottery and clay [12]. These materials were utilized in making up essential items like pots, cups, and cookware. The Badarian culture (4400-4000 BCE) emerged in Al-Badari, upper Egypt, focusing on agriculture and spreading widely, which led to diverse heritage items including pottery, wooden linings, paneling, coffins, and ivory tableware and bangles [13,14]. The Naqada culture (4000-3000 BCE) along the Nile valley saw sustainable urban and economic growth through advanced agriculture, hunting, and trading, with innovations in pottery, functional tools, mud-brick buildings, and the use of copper, gold, silver, and faience for various purposes [15]. The Egyptian civilization became highly developed in many areas of the arts and crafts over its long history [16]. So here is a list of some of the materials used in different categories. ***) Stoneworking:** Ancient Egyptians used limestone, sandstone, greywacke, calcite, schist, diorite, granodiorite, granite, basalt, and quartzite for statues, temples, and other structures, employing copper saws and drills with abrasive sand, and dolerite hammer stones, as evidenced by the unfinished obelisk in Aswan, fig. (2-a) [17]. ***) Pigments and paints:** Egyptian pigments, derived from minerals such as gypsum for white, carbon for black, and ochre for reds and yellows, were likely applied using egg tempera, gums, and resins, as illustrated by ancient color palettes, fig. (2-b) and paintings, fig. (2-c) [17]. ***) Woodworking:** Due to the knots and irregular graining of local woods like tamarisk, acacia, and sycamore, Egyptians imported conifer wood from Lebanon and Syria for larger projects, as demonstrated by ancient woodwork, fig. (2-d) and woodworking tools, fig. (2-e) [17]. ***) Jewelry and metalworking:** Egyptians created vases, amulets, and statues using steatite and faience, and often used gold and silver in religious artifacts, with gold seen in items like Tutankhamun's funerary mask, fig. (2-f), symbolizing the flesh of gods, and silver representing their bones, as shown by ancient accessories, fig. (2-g) [17].

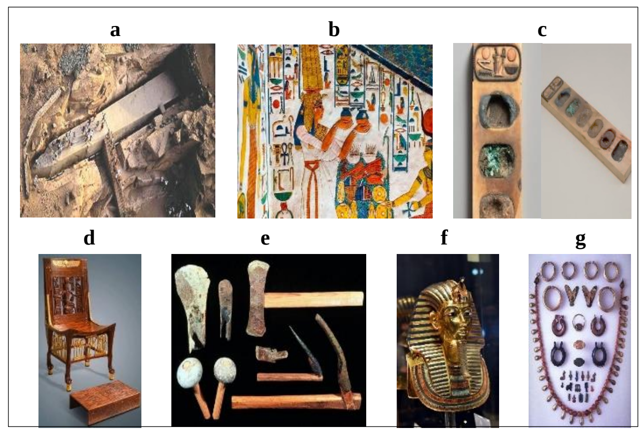


Figure (2) **a.** unfinished obelisk Aswan Quarries [18], **b.** ancient Egyptian paintings [19], **c.** an ancient Egyptian color palette [20], **d.** an ancient Egyptian woodwork [21], **e.** ancient Egyptian woodworking tools [22], **f.** Tutankhamun's funerary mask [23], **g.** ancient Egyptian accessories [24]

Accordingly, we aim to implement and develop a material classifier with adequate complexity and sufficient recognition accuracy. The adequate complexity will allow the usage in real-time applications and portable devices with limited computational capacity. In this work, MobileNet-V3 and ResNet-50, which are light-weight architectures, are chosen to be trained on classifying items of ancient Egypt including items from the prehistoric period according to seven materials, and the main contribution points can be summarized into: *Classifying the tangible items of cultural heritage according to their materials*. Employing MobileNet-V3 and ResNet-50 architectures in the context of Egyptian cultural heritage classification. The remaining parts are organized as follows. The literature review is presented in section 2. The methodology and implementation details are addressed in section 3, which includes the background in section 3.1, the proposed models in section 3.2, models training in section 3.2.3, and the dataset in section 3.2.4. In section 4, evaluation criteria are presented, and the results are discussed, including MobileNet V3 training results in section 4.1 and ResNet training results in section 4.2. Finally, the conclusion is summarized in Section 5.

2. Related Work

Classifying the items of cultural heritage helps in preserving, studying, and interpreting them. Accordingly, there has been an increasing interest in developing machine learning models for classifying these items in their digitalized form. Many cultural heritage classification techniques based on deep learning and traditional machine learning approaches were previously developed and tested [25]. However, we are going to address in this section the studies that adopted deep learning classification techniques which are related to our work where the deep neural networks (DNNs) have proven their efficiency. Authors in [6] were interested in classifying images of buildings with architectural heritage value. Two convolutional neural networks (CNNs): Inception V3 [26] and AlexNet [27] were adopted beside other two residual networks: ResNet [28] and Inception-ResNet-v2 [29]. A new dataset of around 10,000 images was compiled in their study and divided into 10 different types of architectural cultural heritage. The conducted experiments involved evaluating the utility of training these networks from scratch versus only fine-tuning pre-trained versions of them. ResNet yielded the best performance in terms of full training while Inception-ResNet-v2 showed outstanding classification in terms of fine-tuning. In [30], the paper presented famous Indian monuments classification based on the Inception V3 model. The authors utilized a dataset generated using a web crawler where it contained 2600 images. After retraining the last layer of the adopted architecture and then testing the performance on 20 images, the model achieved outstanding accuracy. Moreover, authors in [31] showed interest in the Indian monuments where they introduced a framework of crafted features and deep convolutional neural network architecture for classification. The experiments were carried out on a manually acquired dataset, where 100 different monuments were considered for classification. Classification among three different architectural styles of buildings of the Mexican cultural heritage was done in [32]. The used cultural heritage images were extracted as frames from raw video content. Due to the different view perspectives that the frames came with, a saliency-driven approach was done before training two convolutional neural network (CNN) architectures, GoogLeNet and AlexNet on the classification task. The experimental results elaborated that this visual attention approach increased data quality, and hence, better classification results were obtained. In [33], authors investigated the performance of DNNs on different art classification problems. Due to the lack of available training data, two transfer learning approaches: off-the-shelf and fine-tuning, were followed throughout their study. Four pre-trained architectures: VGG19 [34], Inception-V3, Xception [35] and ResNet50 [36] were experimented while two datasets based on different heritage collections were utilized. The results showed that the finetuning approach outperformed the off-the-shelf one, nevertheless, the latter was effective in material and artwork classifications. Different formats of digitalized items from Indonesian cultural heritage were classified using DNNs in [37]. CNN and recurrent neural network (RNN) techniques were utilized for classification, where CNN was used with images, audio, and videos while RNN was with texts. The dataset included 100 files in each format divided into five categories. RNN showed high performance during testing on text data, while CNN achieved reliable accuracy except for audio classification. Furthermore, in [7], weathering type recognition and classification were introduced for items of cultural heritage. The images used were obtained from eleven different structures and divided into nine categories. In order to classify between these categories, artificial neural network (ANN) and CNN methods were implemented. The results showed that CNN outperformed ANN by achieving a faster and more accurate classification performance. Also, another DNN was applied in [38] to classify images of architectural heritage belonging to ten different categories.

3. Methodology

In this section, MobileNet and ResNet-50 are discussed, followed by our model and the dataset used. Applying image classification on the smartphone requires a lightweight algorithm. MobileNet and ResNet are lightweight Convolution Neural Network which is suitable for mobile phone applications. MobileNet has three versions. Each of them is an enhancement of the previous version.

3.1. *Background*

Classification of the cultural heritage items utilizing deep learning has been proved effective. The researchers have investigated the capability of diverse DNN architectures, including Inception V3, AlexNet, ResNet, and Inception-ResNet-v2, for classifying architectural heritage images [6], Indian monuments [30], and Mexican architectural styles [32]. Specifically, it has been found that fine-tuning of pre-trained models such as VGG19, Inception-V3, Xception, ResNet50, etc. are particularly well suited to art classification [33]. Further, CNNs and RNNs have been effectively employed in classifying various formats of Indonesian cultural heritage [37].

3.2. *The proposed models*

3.2.1. MobileNet

MobileNet V1 is an enhancement for CNN, such that as shown in fig (3-a) it divides the standard CNN into two convolutions which are depthwise convolution and 1×1 pointwise convolution. As fig (3-b) shows, the depthwise convolution works as a filter for each input channel; then the pointwise convolution combines the output of the depthwise convolutions as shown in fig (3-c). This will lead to a decrease in the model size and computation size [39]. MobileNet V2 uses inverted residual and linear bottleneck along with depthwise convolution. As fig (3-d). Figure fig (4-a & b) show, instead of having the skip connection followed by compression to the input before passing it to the layers then it is expanded in the output with the same size as the input, an inverted residual is used which the skip connection is followed by an expansion to the input then passing to the layers and then it is squeezed in the output to be the same size as the input. The inverted residual is used to pass gradients across the layers. To prevent losing data in low-dimensional space due to non-linear layers, linear bottlenecks are inserted. The linear bottleneck is a 1×1 convolution with linear activation. As shown in fig (4-c) using linear bottlenecks has higher performance than non-linear bottlenecks [40,41].

a
b
c

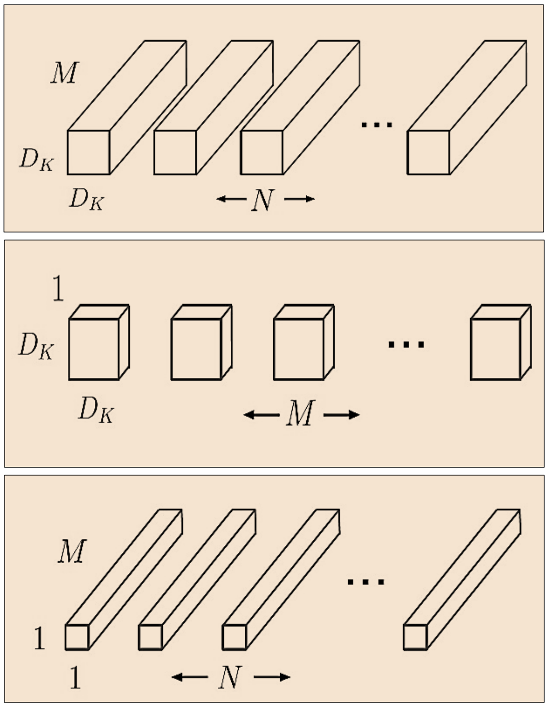


Figure (3) **a.** standard convolution [39], **b.** depthwise convolution [39], **c.** pointwise convolution [39]

a
b
c

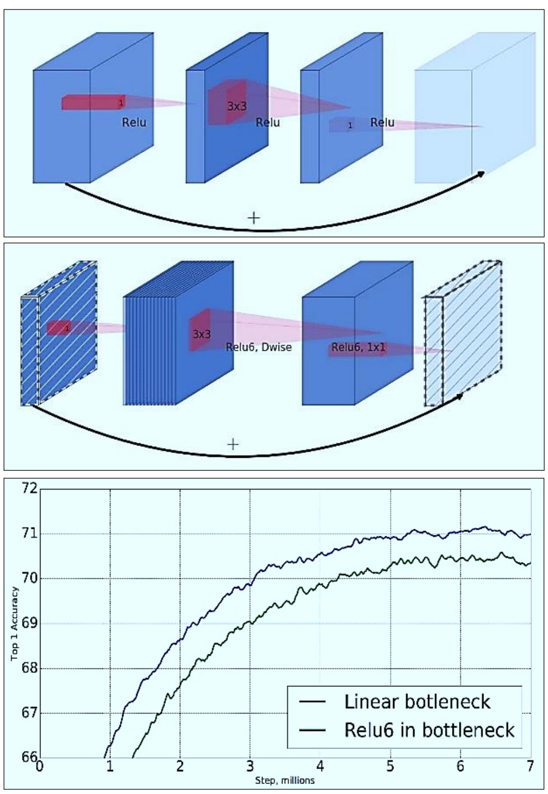


Figure (4) **a.** residual blocks [40], **b.** inverted residual blocks [40], **c.** linear and non-linear bottlenecks performance [40]

MobileNet V3 uses Network Architecture Search (NAS) for optimization by finding the best architecture then NetAdapt is used for fine-tuning each layer. NAS to find the best architecture, uses reinforcement learning to hierarchal search in a constructed search space for the neural network architecture with MnasNet-A1 as an initial model. Then, the NetAdapt algorithm starts with a seed network architecture provided by NAS, then, in each step, it generates a group of proposals each of them is a modification for the architecture, and each of them enhances the latency of the previous step, then using the model trained in the previous step, a new architecture is proposed then evaluated to select the best one. The RELU activation function is replaced by the swish function. Because of the usage of the swish function to a lot of computational resources, RELU6 is used to approximate the sigmoid function producing an approximation called h-swish [41, 42].

$$swish(x) = x \, . \, \sigma\,(x) \qquad \textbf{(1)}$$

$$h - swish[x] = x \frac{RELU6\,(x+3)}{6} \qquad \textbf{(2)}$$

MobileNet-V3 represents a significant advancement in neural network architecture tailored for mobile and embedded systems. With a compact size of 15.3 MB and notable accuracy achievements, MobileNet-V3 emphasizes efficiency without compromising performance. It achieves this through depthwise separable convolutions and inverted residuals, which reduce computational complexity by minimizing parameters and operations. This design choice not only optimizes resource utilization but also enhances speed and memory efficiency, making Mobile Net-V3 ideal for deployment in environments with limited computational resources. Comparative evaluations against other lightweight models like ShuffleNet-v2 and Efficient-Net-b0 highlight MobileNet-V3's competitive edge in balancing size, computational efficiency, and accuracy, reaffirming its suitability for a wide range of practical applications on mobile platforms [50-53]. Compared to heavier models like Inception-ResNet-v2 used in [6], Inception V3 in [30], GoogLeNet and AlexNet in [32], VGG19 and Xception in [33], MobileNet V3, with its lightweight and efficient design, is suitable for mobile applications, offering a practical trade-off between performance and computational demands. Additionally, no previous work has specifically focused on classifying Egyptian artifacts' materials, highlighting the novelty and importance of our study.

3.2.2. ResNet 50

In this work, we use ResNet-50, a deep-CNN architecture for cultural heritage recognition. The ResNet-50 architecture has become a strong example to show that deep networks can be trained with residual learning and solve the lowering accuracy problem in deep-CNN architectures [43]. Also, Resnet50 architecture is used due to the limited resources to train our model making the pre-trained weights important [44]. One of the variants of ResNet (a convolutional neural network) is ResNet50 which has 50 layers. Its layers consist of 48 Convolution layers, 1 MaxPool, and 1 Average Pool layer. The architecture of ResNet50 is shown in detail in fig (5-a). The problem of vanishing gradient (*The vanishing gradient problem happens when there are more layers in the network, the value of the product of derivative decreases until at some point the partial derivative of the loss function approaches a value close to zero, and the partial derivative vanishes* [45]) is solved by ResNet which is based on the deep residual learning framework even with extremely deep neural networks. Regardless of ResNet50 having 50 layers, it has over 23 million trainable parameters which is much smaller than the other existing architectures. The explanation of how ResNet50 works is still being discussed so to understand how it works we have to understand how residual blocks work. Let's say that we want to know the true distribution H(x) considering a neural network block whose input is x. let's demonstrate the difference (residual) between these:

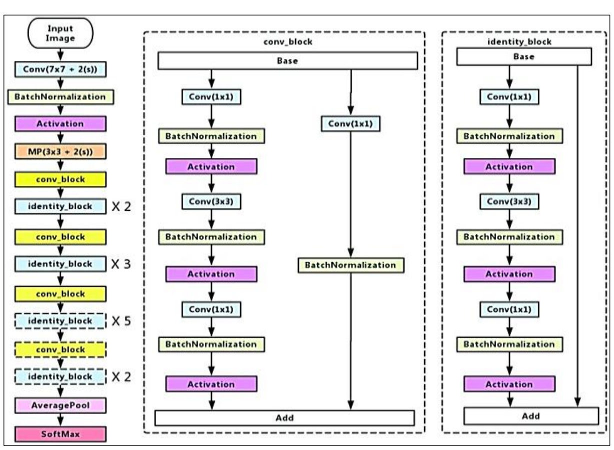
$$R(x) = Output - Input = H(x) - x$$

Rearranging it we get:

$$H(x) = R(x) + x$$

The residual block is trying to learn the true output which is H(x). Taking a closer look at fig (5-b), we notice that the layers are learning the residual which is R(x) due to having an identity connection coming due to x, while in a traditional network, the layers learn the true output which is H(x). Learning the residual of the output and input rather than the input only is observed to be easier. Hence the previous layers are skipped allowing the reuse of activation functions by the identity model, adding no more complexity to the architecture [46]. The complexity analysis of ResNet-50 reveals its high computational demands due to its deep architecture and over 23 million parameters. Despite this, ResNet-50 addresses the vanishing gradient problem effectively through residual learning with residual blocks, focusing on learning residual mappings instead of full mappings. This approach enhances training stability and efficiency while optimizing computational resources without sacrificing accuracy. The model's complexity is also influenced by input resolution, where higher resolutions increase computational requirements across the network [54]. ResNet-50's advantages include reliability, as it is a well-established architecture extensively used in various computer vision tasks compared to models like Inception-ResNet-v2 used in [6], Inception V3 in [30], GoogLeNet and AlexNet in [32], VGG19 and Xception in [33]. It offers better performance due to its deep architecture capable of capturing complex patterns and features. Additionally, ResNet-50 is relatively efficient in terms of computational resources, making it suitable for deployment across diverse hardware platforms, including low-power devices like smartphones and embedded systems [55].

a



b

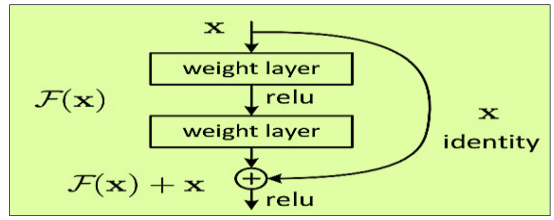


Figure (5) **a.** ResNet-50 architecture [47], **b.** residual learning block [48]

3.2.3. Models training

For the first approach we used the MobileNet V3 pre-trained model, the model's input layer accepts images of size 224× 224 pixels with 3 color channels. From MobileNet, the architecture extracts features from a layer situated six layers before the final output layer then, a dense layer is added on top, configured with 8 units corresponding to the number of classes in the dataset. This dense layer uses softmax activation to produce class probabilities. During training, all layers except the final 15 are frozen to preserve MobileNet's learned features while reducing trainable parameters. The model is compiled using the Adam optimizer with a learning rate of 0.00001 and optimized for sparse categorical cross-entropy loss. Training includes early stopping to prevent overfitting, and it utilizes a batch size of 7. The execution GPU time for the entire dataset ranges from about 2 to 3 hours. For the second approach we employed a fine-tuned ResNet50 convolutional neural network. ResNet50 model is the base model. Its initial layers, including convolutional and pooling layers, are frozen to retain the learned feature extraction capabilities from ImageNet. On top of ResNet50, we added a Global Average Pooling layer to reduce the spatial dimensions of the feature maps followed by a dense layer with 1024 units and ReLU activation to capture more features. The final layer consists of a dense softmax layer with a number of units equal to the classes in our dataset. During training, the model is compiled using the Adam optimizer with a learning rate of 0.00001 and applied categorical cross-entropy loss. Training includes early stopping to prevent overfitting, and it utilizes a batch size of 7. The execution GPU time for the entire dataset ranges from about 3 to 4 hours. The values of the training parameters like batch sizes and learning rates used for MobileNet V3 and ResNet-50 reflects considerations tailored to each model's architecture and computational demands. MobileNet V3, recognized for its efficiency in computational resources, benefits from a smaller batch size of 7, ensuring efficient memory utilization and stable parameter updates during training. This batch size strikes a balance between computational efficiency and model convergence. Similarly, ResNet-50, despite its deeper and more complex structure, also uses a batch size of 7, leveraging optimizations that accommodate this size effectively. Both models employ a learning rate of 0.00001 to fine-tune their pre-trained weights gradually. These parameters have been selected based on empirical testing and have consistently demonstrated optimal results in balancing model performance and training efficiency.

3.2.4. Dataset

The tangible ancient Egypt heritage is rich with various items including monuments, sculptures, furniture, accessories, and many others. These varieties in the existing artifacts are due to the abundance of materials and minerals that are found in the fertile land of Egypt. The Global Egyptian Museum (GEM) is a long-term project, carried out under the aegis of the International Committee for Egyptology (CIPEG), provides a website [49] which aims to collect the cultural heritage items of ancient Egypt into a global virtual museum. This website can be freely accessed at any time and from any place which gives more accessibility to a wide range of items. The website allows two browsing modes: basic and advanced. The advanced mode permits looking for images of specific items according to category, material, date, archaeological site, ancient god, historical king, and present location. In this approach, eight materials were chosen to be fed to MobileNet for recognition and classification. The materials are bronze, clay, limestone, wood, faience, pottery, granite, and gold. The reasons behind selecting these materials in specific are their originality, essentiality, importance, and popularity in the Egyptian cultural heritage. The material types along with the corresponding number of collected images in each are listed in tab. (1) while samples from the used images are shown in fig (6). From each of these material classes, 80 images were randomly selected for validation and another 160 images for testing. The data preprocessing steps implemented involve several key processes to ensure the effectiveness of the training process. The dataset is organized into separate directories for training, validation, and testing sets, with ratios of 81%, 9.5%, and 9.5%, respectively. Data augmentation is then applied, which includes random horizontal and vertical flipping, as well as random rotations, to artificially diversify the training images and enhance model generalization. Images are resized to a uniform size of 224×224 pixels. Additionally, feature-wise standard normalization is applied to further normalize the input data. Throughout these steps, file operations ensure that images are correctly formatted and organized within their respective directories.

Table (1) the number of images in each class of the used data.

Material	Total number of images
Bronze	655
Clay	467
Limestone	856
Wood	659
Faience	1220
Pottery	1086
Granite	879
Gold	805

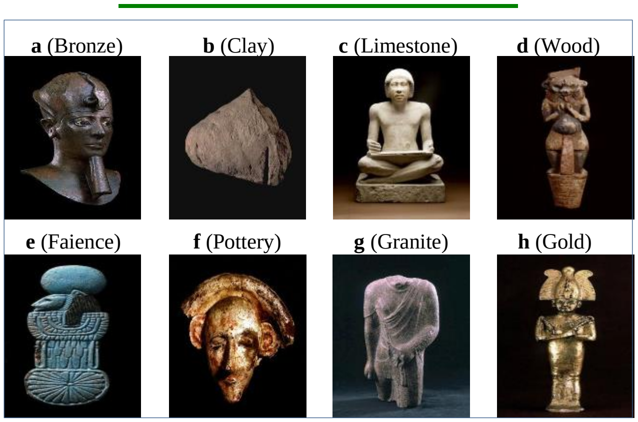


Figure (6) sample images from the used dataset [49].

4. Results

4.1. *MobileNet V3 training results*

The model has been trained for 50 epochs. Accuracy is the main used metric as the model is used in classification. Figure (7-a) shows the changes in the training and validation accuracy in each epoch having the training accuracy of 99.6 % with validation accuracy equals 78.75 %. Figure (7-b) shows the changes in the training and validation loss which has 0.082 for the training loss and 0.788 for the validation loss. The confusion matrix shown in fig (7-c) was the output of testing the model using the testing set. It shows how the model performs in each class. The model best predicts class 6 which predicted 148 out of 160 images, and the least correctly predicted class is class 3 which predicted 93 out of 160 images. The model has been tested using the images in fig (7-d) which are from the prehistoric periods [49] and they were correctly classified such that fig (8-a) was classified as Limestone and the other images in fig (8) were classified as Pottery.

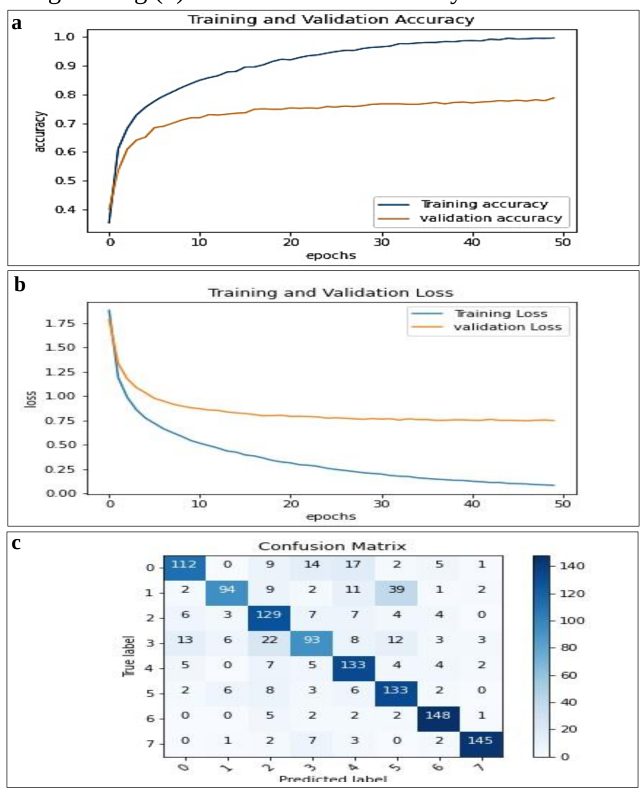


Figure (7) **a**. training and validation accuracy, **b**. training and validation loss, **c**. confusion matrix

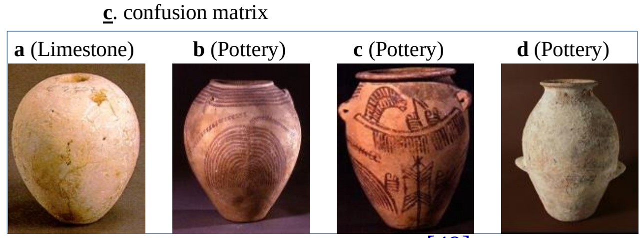


Figure (8) samples of prehistoric testing images [49]

4.2. *ResNet training results*

The model has been trained for 60 epochs. Accuracy is a very important part of the model as the model is used in classification. Figure (9-a) shows how the training and validation accuracy changes in each epoch knowing that the training accuracy is 96.62% and the validation accuracy is 83.23%. Figure (9-b) shows how the training and validation loss changes in each epoch knowing that the training loss is 11.10% and the validation loss is 73.58%. The validation accuracy of the MobileNet V3 model, at 78.75%, lags behind the training accuracy of 99.6%, while the validation accuracy of the ResNet model, at 83.23%, also lags behind the training accuracy of 96.62%, indicating potential overfitting. This difference suggests the models are learning the training data too well, including its noise, which hinders their performance on new data. Overfitting can stem from the models' complexity and insufficient or unvaried training data. To address this, several strategies can be employed such as using techniques like over sampling, under sampling, or a combination of both, to balance the class distribution and ensure that each class has the same number of samples, and applying regularization techniques like dropout or L2 regularization which can further help the models generalize better to unseen data, thereby improving validation accuracy.

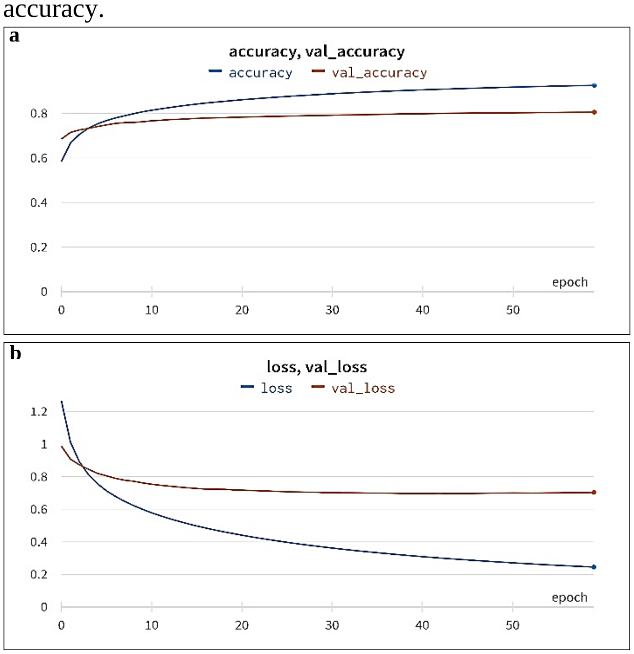


Figure (9) **a.** training and validation accuracy, **b.** training and validation loss

5. Discussion

Using machine learning models to recognize and classify heritage items can be reliable, especially if these models are trained on a sufficient dataset with precise separation between the data classes. In this work, MobileNet V3 and ResNet-50 were used as lightweight architectures to be compatible with real-time operation on mobiles. After working on the training strategy, models for classifying cultural heritage items according to seven different categories and eight different materials. This was challenging due to the wide range of features found in the classes of the dataset images. However, after different trials and experiments, we achieved robust, high-performance models that can be used in real-time. The results show that the MobileNet V3 and ResNet-50 models can classify the items of the images of the artifacts according to the materials sufficiently with high accuracy exceeding 96%. Both models' curves showed more uniform training without fluctuation when the model was trained in 8 different classes for 50 epochs. However, the validation accuracy still needs improvement to achieve better performance. Increasing the number of epochs can be a good idea. Yet, the plots show relatively high saturation in the epochs, giving the intuition that increasing the number of epochs will not significantly improve the validation accuracy. Accordingly, increasing the data is more adequate to be tried. So, this is the future work of this paper: to increase the size of the dataset.

6. Conclusion

MobileNet has three versions. Each version is an enhancement of the precedence one. MobileNet V1 is an enhancement for the Convolution neural network as it uses depthwise and pointwise convolution. MobileNet V2 is an enhancement of V1 as it uses inverted residual and linear bottleneck. MobileNet V3 uses Network Architecture Search and NetAdapt as well as the swish activation function for optimization. ResNet-50 is a deep network that has 50 layers. The deeper the network the better for neural networks but that makes these networks harder to train but the structure of ResNet50 makes training of net-works much easier and allows them to be much deeper, as a result, the performance in different tasks becomes more efficient. The model has been trained on a dataset consisting of 8 classes achieving 99.6%, 78.75%, 99%, and 80% for the training and validation of MobileNet-V3 and ResNet-50 respectively.

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