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Examination Malpractice Panacea: A Deep Learning Approach Using MobileNetV2

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ABSTRACT : *Examination malpractice is like a cancer that has eaten deep into the mainstream of Education in secondary and tertiary institutions in developing countries such as Nigeria. If not tackled holistically tends to destroy the aim behind achieving it. In this work, the use of deep learning in facial recognition using the MobileNetV2 model was proposed as a game changer towards the curbing of examination malpractices (impersonation) in the institution of learning. The result obtained after the model training indicates strong performance with an accuracy of 0.944 which is a little bit shy of the perfect accuracy of 1.00. Technically, this showed that when implemented digitally in learning institutions, it will be able to facially recognize students who collude with one another for impersonation, thereby significantly reducing examination malpractices.*

KEYWORDS: *deep learning, examination malpractice, facial recognition, mobilenetv2*

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I. INTRODUCTION

The Educational sector which is a critical part of any society is tasked with the responsibility of developing reliable manpower for the ever-increasing industries and services in the society.

A crucial part of the education system is examination, where students are appraised to validate the knowledge, they have acquired over time. However, with the rising wave of examination malpractice in the educational sector, especially among developing countries; students now improvise malicious ways of getting certified for the knowledge they did not acquire. This trend is the reason behind the common belief that examination is no longer a true test of one's ability. Culprits would rather pay impersonators or cheat in examination halls than study for the exams. A case study on the Senior School Certificate Examinations (SSCE) conducted by the National Examination Council of Nigeria showed that 40,805 malpractice cases were reported in 2000. By 2007, this figure grew to 465,582 which is about a 167% increase [1]. In 2012, the same country was ranked number one in the Global Examination Malpractice Index [2]. In 2019, the results of about 11.33 percent of the total candidates who sat for the West African Examination Council (WAEC) examination were withheld because of mass cases of examination malpractice in various centres all over West Africa [3]. Trends like this have resulted in growing distrust in the education sector in most developing countries and if left unchecked will result in colossal damage to the educational sector.

Accurate facial recognition technology has the potential to significantly curb examination malpractice, a pervasive issue plaguing educational systems worldwide. In Nigeria, for instance, examination malpractice has become increasingly sophisticated, with students employing various methods to cheat, including digital cheating [4]. There are different forms of examination malpractices which include: bringing in unauthorized materials, collusion between students, invigilators, and examiners, examination leakage, mass cheating, impersonation, and digital cheating.

Currently, most schools employ the use of student Identity cards and attendance registers to usher students into examination halls. This method partially checks for impersonators and other illegal entrants. Also, various researches have been carried out to curb examination malpractice using technology. Closed-circuit television (CCTV) cameras, biometric technologies, and facial recognition systems are being employed to solve this problem. The researchers in [5] designed a virtual invigilator system that monitors and records real-time activities in an examination environment. This system also alerts invigilators of suspected actions that violate set rules for the examination. Devices for detecting the presence of mobile phones, personal digital assistants (PDAs), and other network-adapted devices were used by invigilators [6]. This helps to identify candidates who sneaked into the examination hall with such devices as they can be used to perpetuate examination malpractice. Signal jammers were adopted by [7] to jam radio and wireless signals so that candidates who successfully sneaked their devices into the hall wouldn't effectively use them to communicate inside the hall. Computer-based tests (CBT) are also being used to reduce the chances of candidates cheating in exams by using random questions and time-based entries. The aforementioned solutions have certain shortfalls which are addressed by our proposed solution. For instance, solutions such as the use of signal jammers and mobile phone detectors that do not integrate students' biometrics cannot effectively check for impersonation. The use of CCTV cameras without a facial recognition system cannot also check for impersonation. In this work, we developed a cost-effective, deep-learning based solution, which would implement a facial recognition algorithm for student identification and authentication, thus eliminating impersonation.

II. MATERIALS AND METHODS

A. MATERIALS

This work/project involved a combination of hardware and software tools, as well as a dataset of student images collected from different locations around the campus.

Hardware: The computational tasks for the project were executed using a high-performance graphics processing unit (GPU) available on Google Colab. The use of a GPU was essential for accelerating the deep learning tasks, including training and fine-tuning the MobileNetV2 model. Google Colab's cloud-based environment provided the necessary computational resources to handle the complexities of model development, training, and testing.

Software: Several software libraries /tools known as deep learning frameworks [8] were utilized to complete this project, each serving a specific purpose in handling data, building the model, and running the necessary experiments, some of the utilized frameworks include TensorFlow, Keras, OpenCV (CV2), Matplotlib and NumPy.

TensorFlow: TensorFlow was the primary machine learning framework used to construct, fine-tune, and train the MobileNetV2 model. It offers comprehensive support for deep learning operations and is widely used in face recognition applications due to its efficiency and scalability.

Keras: Integrated with TensorFlow, Keras was used for building the neural network architecture and managing the model training process. Its user-friendly interface and support for transfer learning were critical to the success of the project.

OpenCV (CV2): OpenCV is a powerful library for computer vision tasks. In this project, it was used for processing the input images, including resizing, augmenting, and normalizing them. OpenCV was also essential for loading images from Google Drive and preparing them for model input.

Matplotlib: Matplotlib was employed for visualizing the model's performance during training. It provided graphical representations of accuracy and loss over time, which were essential for monitoring overfitting and optimizing the training process.

NumPy: NumPy was used to perform various numerical operations and handle the arrays of image data. It was instrumental in reshaping and transforming image inputs for the neural network.

Google Colab: The entire development and training workflow took place on Google Colab, a cloud-based platform that provides access to free GPU resources. It facilitated the integration of other tools such as TensorFlow, OpenCV, and Google Drive, providing a seamless environment for model training and testing.

Dataset: The dataset consisted of images of students collected from various campus locations. Each individual was represented by two images, making the dataset suitable for the two-shot learning approach employed in this project. This dataset was hosted on Google Drive for easy accessibility during model development and experimentation.

Images: The images featured diverse facial expressions, lighting conditions, and orientations to make the model more robust and capable of handling variations in real-world settings.

Storage: Google Drive was used to store the dataset, allowing for direct access during training on Google Colab.

B. METHOD

This section explains the steps taken to prepare the data, fine-tune the model, and evaluate the results. It covers data preprocessing, model architecture adjustments, training, and evaluation. Figure 1. shows the workflow through which these steps are achieved.

Preprocessing

Preprocessing is a critical step in ensuring that the input images are formatted consistently and appropriately for training. The following steps were taken to preprocess the dataset:

1) Image Resizing: All images were resized to 160x160 pixels to match the input requirements of the MobileNetV2 model, see Table 1. Uniform image dimensions are crucial to ensure that the model receives consistent data and reduces the computational load during training.
2) Data Normalization: Each image's pixel values were normalized by scaling them between 0 and 1. Normalization ensures that the input values are within a similar range, which helps the neural network converge faster during training by reducing the likelihood of vanishing or exploding gradients.
3) Image Loading and Processing: OpenCV was used to load the images from Google Drive, resize them, and apply augmentation. The images were then converted into NumPy arrays, which were fed into the model for training. This process ensured that the images were properly formatted for input into the neural network.

Feature Selection

Feature selection in this project was handled through the MobileNetV2 model, which had been pre-trained on the ImageNet dataset. The primary goal was to leverage the model's pre-existing feature extraction capabilities while adapting it to the face recognition task.

Freezing Layers for Transfer Learning: The initial layers of the MobileNetV2 model, which are responsible for detecting general features like edges and textures, were frozen during training. Freezing these layers allowed the model to retain its ability to extract basic visual features from the input images, reducing the risk of overfitting by preventing unnecessary modifications to these generalized features.

Custom Layers for Face-Specific Features: On top of the frozen layers, custom layers were added to allow the model to learn more specific features related to the faces in the dataset. The GlobalAveragePooling2D layer reduced the spatial dimensions of the feature maps, while fully connected layers were used to classify the students' faces.

The combination of pre-trained layers and custom layers provided a balance between general feature extraction and task-specific learning, which helped improve the model's accuracy.

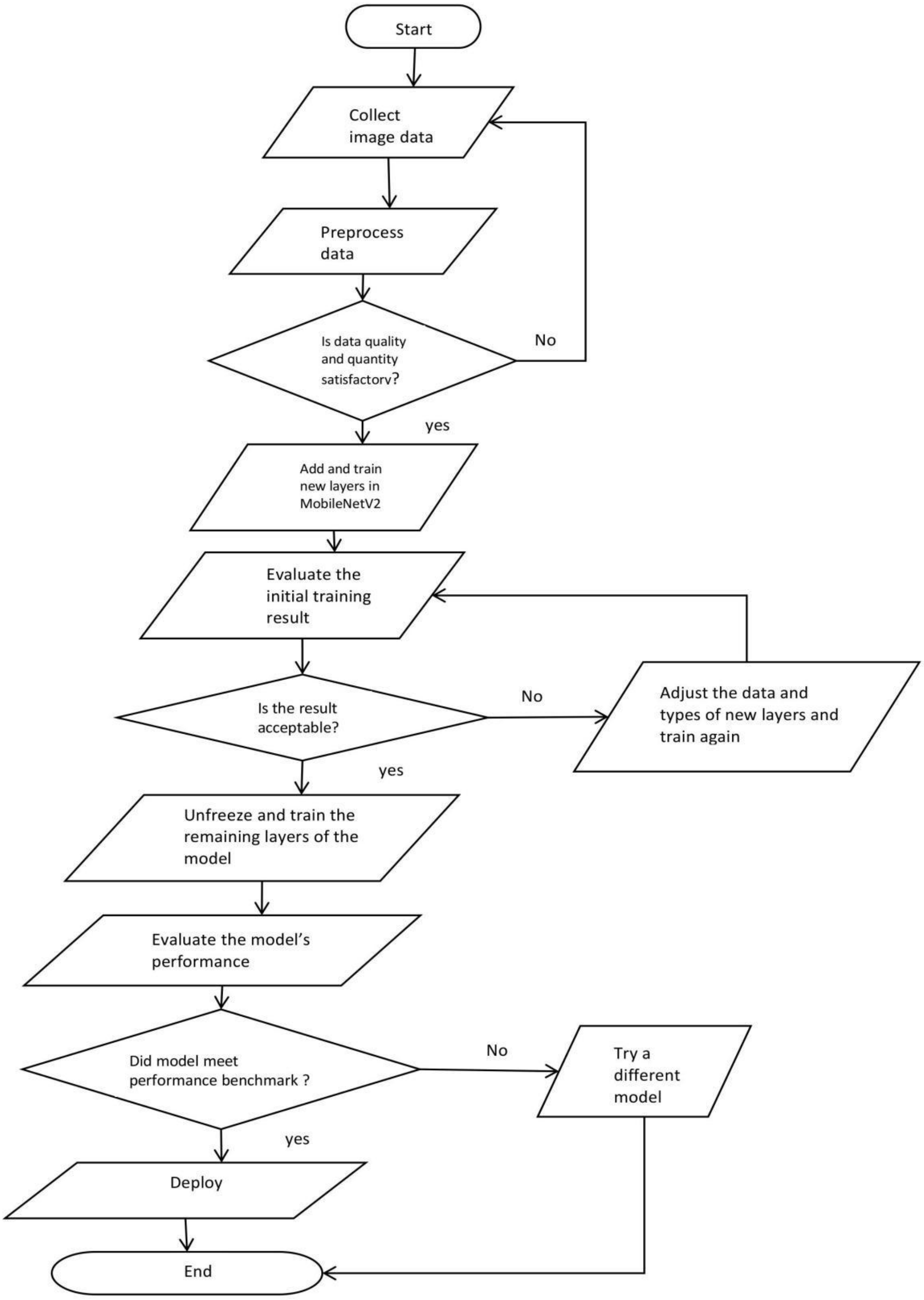

Fig. 1. Flowchart illustrating the work flow or method

Table. 1. Summary of the MobileNetV2 model

```
Model: "functional"
```

Layer (type)	Output Shape	Param #
input_layer_2 (InputLayer)	(None, 160, 160, 3)	0
mobilenetv2_1.00_160 (Functional)	(None, 5, 5, 1280)	2,257,984
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
batch_normalization (BatchNormalization)	(None, 1280)	5,120
dense (Dense)	(None, 128)	163,968
batch_normalization_1 (BatchNormalization)	(None, 128)	512
dense_1 (Dense)	(None, 10)	1,290

```
Total params: 2,428,874 (9.27 MB)
Trainable params: 168,074 (656.54 KB)
Non-trainable params: 2,260,800 (8.62 MB)
```

Model Training

The training process involved two stages: initial training of custom layers and fine-tuning of the entire model.

1. Initial Training: The custom layers were first trained while keeping the pre-trained layers of MobileNetV2 frozen. This allowed the model to focus on learning features specific to the face recognition task without modifying the general features learned from the ImageNet dataset. The model was trained for ten epochs, achieving an accuracy of 1.00 and a loss of 0.169. Although perfect accuracy was achieved during initial training, concerns arose regarding overfitting due to the small dataset.

2. Fine-tuning: In the fine-tuning phase, the frozen layers of the MobileNetV2 model were unfrozen, and the entire model was retrained on the same dataset. Fine-tuning helps the model adjust its pre-trained features to the nuances of the specific dataset, allowing it to improve its performance. After a few additional epochs, the model's accuracy dropped slightly to 0.944, and the loss increased to 0.776, indicating a small degree of overfitting.

Optimizer and Loss Function: The stochastic gradient descent (SGD) optimizer was used to update the model's weights, with an initial learning rate of 0.001. The categorical cross-entropy loss function was applied to compute the difference between the true class labels and the predicted class probabilities. This combination of optimizer and loss function ensured that the model converged effectively during both initial training and fine-tuning.

Model Testing and Evaluation

The model's performance was evaluated using key metrics, including accuracy and loss, which were tracked throughout both training phases.

1. Accuracy: During initial training, the model achieved perfect accuracy (1.00), meaning it correctly classified all images in the training dataset. After fine-tuning, the accuracy dropped slightly to 0.944, which still indicates strong performance but suggests that the model may have started overfitting the training data due to the small dataset size.

2. Loss: Loss measures the difference between the predicted outputs and the actual labels. During initial training, the model's loss was 0.169, and after fine-tuning, it increased to 0.776. The increase in loss during fine-tuning suggests that the model struggled to generalize beyond the training dataset.

3. Overfitting: Overfitting is a common problem when training models on small datasets. The perfect accuracy in initial training and the slight drop in accuracy during fine-tuning indicates that the model may have memorized the training data rather than generalizing to new examples. To mitigate this issue in future iterations, techniques such as early stopping or L2 regularization could be employed to ensure better generalization.

III. RESULT AND DISCUSSION

The fine-tuned MobileNetV2 model showed strong performance in recognizing faces for class examination attendance purposes. The initial training phase resulted in a converged perfect accuracy of 1.00 at the 4th epoch, as seen in figure 2, but the fine-tuning phase introduced a slight decrease in accuracy to 0.944 at the 6th epoch, as seen in figure 3, accompanied by an increase in loss. The decline in performance during fine-tuning suggests some degree of overfitting, as the model became overly adapted to the training dataset.

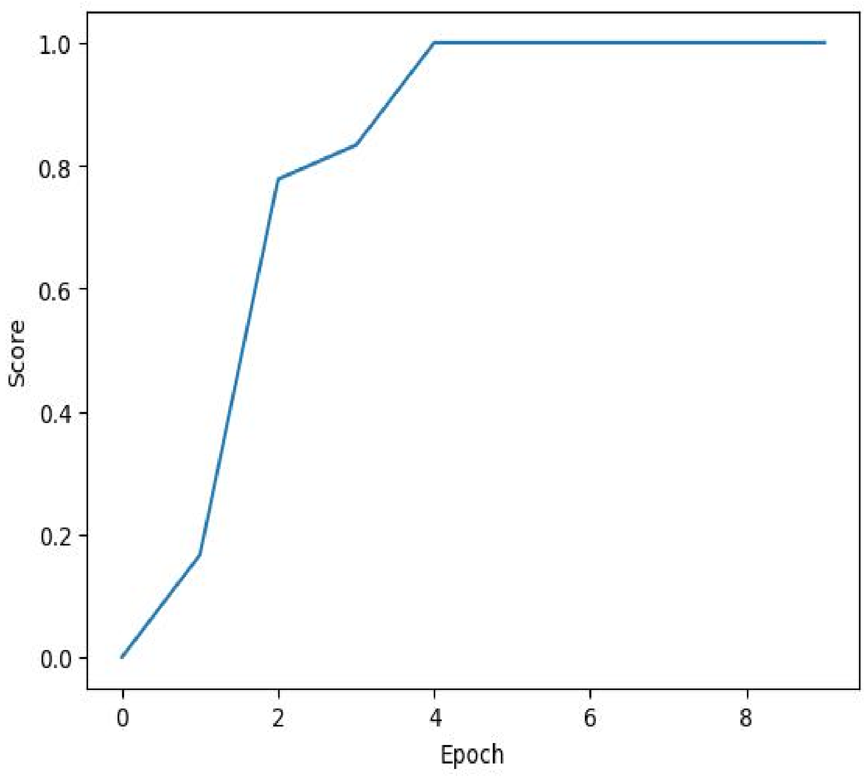

Fig. 2. Graph showing model performance during initial training

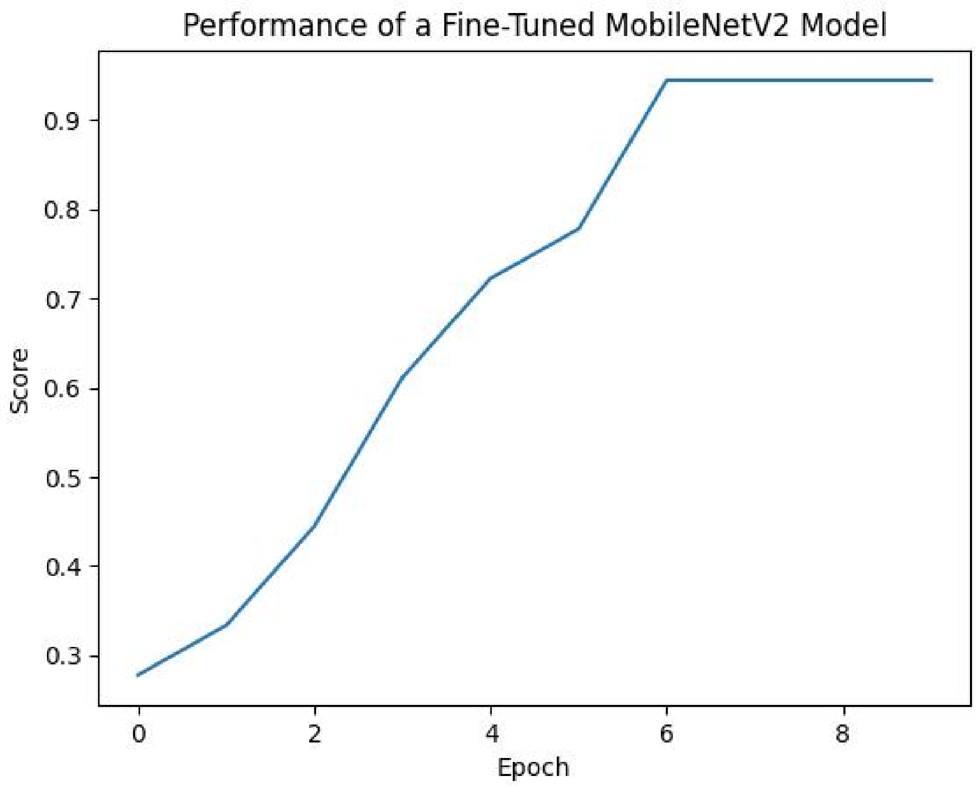

Fig. 3. Graph showing model performance at the second stage of training (fine-tuning)

1. Accuracy and Loss Analysis: The accuracy curve demonstrated rapid convergence during the initial training epochs, indicating that the model quickly learned the distinctive features of the dataset. However, the slight decrease in accuracy during fine-tuning suggests that the model may have memorized the training data rather than generalizing well to new, unseen instances. The increase in loss during fine-tuning further supports this hypothesis.

2. Overfitting Considerations: Overfitting occurs when the model learns the noise and details of the training data too well, resulting in poor performance on new data. The limited number of images in this project (only two per class) made overfitting a significant risk. Despite this, the model's overall performance was satisfactory for the intended task, although strategies like early stopping or L2 regularization [8] could be employed in future work to mitigate overfitting.

IV. CONCLUSION

The use of deep learning in facial recognition has brought about significant advancements across various sectors, more recently in automated attendance systems in educational settings. In this work, we leverage the MobileNetV2 model, which was pre-trained on the large-scale Imagenet dataset, and adapt it to a specialized task of recognizing student faces during examination monitoring and attendance to curb impersonation which is a form of exam malpractice. It was established that the trained model performance was significant because it gave an accuracy of 0.944 out of 1.00 which was satisfactory for the intended task.

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