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Deep Transfer Learning Approach for Student Attendance System During the COVID-19 Pandemic

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Abstract: Marking students' attendance has been a challenge during the COVID-19 pandemic. It is a time-consuming task due to the abnormally high number of students present during a learning session; many studies have been proposed to improve the system. However, there are still issues with each of these systems; we have employed deep transfer learning techniques using six pre-trained convolutional neural networks. We created a dataset of faces with masks and we used this dataset to assess six Convolutional Neural Network (CNN) models. We increased the training samples to improve the performance of the pre-trained models. The latter allows us to build a masked face recognition model of learners during a learning session. Due to the COVID-19 pandemic, students don facemasks to safeguard their own well-being and mitigate the spread of the virus. This has created a problem that did not exist before. The experimental findings reveal that pre-trained models, specifically caption and InceptionResNetV2, exhibit outstanding proficiency in precisely identifying faces with masks and require minimal training time.

Keywords: CNN, Computer Vision, COVID-19, Deep Transfer Learning, Student Attendance System of Absence Records by Using Facial Recognition to Detect and Identify Students' Faces

Introduction

An intelligent system that detects students' presence in class is an application that enables teachers and school administration to automate the process of recording attendance during learning sessions and exams.

This system facilitates the administration of attendance in educational institutions through the utilization of face detection and facial recognition technology. The system was developed to allow teachers to limit the time spent on registering student absences. The interaction with students during registration, in addition to saving time on manual and repetitive work, minimizes loss of productivity. During the Covid-19 pandemic, the mandatory use of masks became prevalent in areas where people gather, particularly in educational institutions and training centers.

This system enables the detection of students' faces while wearing masks and performs face detection and facial recognition. The intelligent student attendance system scans documents and optimizes the management of absence records by using facial recognition to detect and identify students' faces. This study presents an approach for recording student attendance in a classroom utilizing deep transfer learning. The primary achievements of this study can be encapsulated as follows:

1) A data processing stage involves employing the MaskTheFace technique to apply a virtual mask to each image in the pins face recognition dataset. Furthermore, a data augmentation method is utilized to enhance the training samples
2) The use of six pre-trained convolutional neural networks (Xception, InceptionResNetV2, MobileNetV2, DenseNet201, ResNet101V2, and EfficientNetB0) for masked face identification
3) Assessment of the effectiveness of the six networks in identifying student attendance in a classroom learning session amid the COVID-19 pandemic, accomplished through the implementation of transfer learning

The pre-trained convolutional neural networks used in this study exhibit good predictive performance. These Convolutional Neural Networks (CNNs) enable the substitution of the pre-trained network's final "fully-

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connected layer" with a classifier customized for the specific problem at hand, based on the number of classes in the dataset (in our case, 110 classes) and randomly initialized. All layers are then trained on the new images.

The purpose of this study is to design and implement a masked face detection application capable of recognizing faces and recording student attendance during classroom learning sessions, while taking into consideration the COVID-19 pandemic. We utilized artificial intelligence technologies, such as deep transfer learning, to achieve our objectives. Our method involved capturing images of students in the classroom, linking these images to the database to verify their attendance, documenting their presence, and subsequently storing the data. The flow chart of our proposed technique is presented in Fig. 1.

We use a surveillance camera to capture images of students during classroom learning sessions. After capturing the images, we scan them to detect masked faces. Once the masked faces are detected, we extract the faces of individual students from the images. Using a masked face recognition model, we then extract the students' information, such as their names, surnames, and registration codes.

In recent decades, a variety of techniques has been employed for attendance systems. Image processing methods have been integrated into various artificial intelligence strategies, including deep learning, Convolutional Neural Networks (CNNs), and transfer learning (Alhanaee *et al*., 2021).

Deep Learning (DL)

Deep learning is a rapidly advancing field within artificial intelligence that stems from machine learning, empowering machines to autonomously acquire knowledge, as opposed to simply following predetermined rules in programming. Deep learning methodologies have proven to be effective across diverse domains, such as object recognition, image recognition, biomedical and health informatics, chatbots, intelligent robots, and medical imaging applications (Hernández-Blanco *et al*., 2019). Deep learning is a sophisticated system that mimics the human brain and consists of a vast network of artificial neurons that process and store information. It can compare current problems or situations with similar ones in the past, analyze potential solutions, and find the best possible way to solve the problem (Futura, 2023).

Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a specific form of artificial neural network created for the task of image processing and recognition that operates by processing pixel data. These networks serve as robust instruments within the realm of artificial intelligence, employing deep learning to address both generative and descriptive tasks. They often rely on machine vision methods for recognizing images and videos, as well as natural language processing and recommendation systems (Xu and Zhang, 2022). The design of a CNN incorporates a multilayer perceptron system optimized to minimize computational demands. Typically, a CNN comprises several layers, including an input layer, an output layer, and a hidden layer composed of multiple convolutional layers, pooling layers, fully connected layers, and normalization layers (Setialana *et al*., 2021).

Transfer Learning (TL) and Pre-Trained Models

Transfer Learning (TL) refers to a group of methods that enable the transfer of knowledge acquired from solving one problem to another problem. TL mainly involves utilizing pre-trained neural networks as feature extractors. Models that work well on source tasks, such as VGG-16, VGG19, and resnet-50 for computer vision and word2vec, glove in Natural Language Processing (NLP), are essential requirements for TL (Datascientest, 2023).

Transfer learning has been employed in various domains, including medicine, bioinformatics, face recognition, recommendation systems, and speech-emotion recognition (Zhuang *et al*., 2020). For instance, Sapna *et al*. (2021) the pre-trained VGG16 CNN deep learning model was employed to develop the attendance system, with a specific focus on detecting students' faces and recording their attendance.

In the study conducted by Oumina *et al*. (2020), the parameters of three pre-trained deep neural network models (VGG19, caption, and mobilenetV2) were adjusted to identify mask-wearing individuals. Remarkably, the mobilenet-V2 model with SVM integration exhibited outstanding performance, achieving an impressive accuracy rate of 97.11%.

According to Malhotra (2021), the team used transfer-learning technology with the face net model for feature extraction and face verification. After feature extraction, the system stores the output as matched or unmatched during face verification.

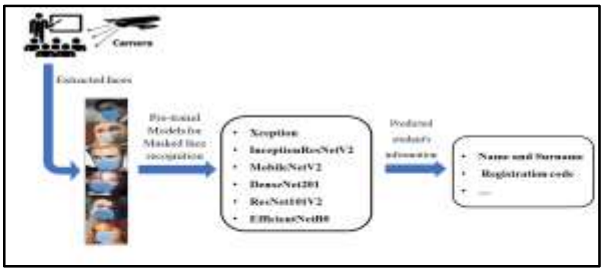

Fig. 1: Flowchart for our proposed system

Table 1: Related work summary

Literature	Methodology	Dataset	Result %
Athanesious *et al*. (2019)	VGG network	Self-contained 13063 images without mask	94.66(Acc.)
Alhanaee *et al*. (2021)	AlexNet CNN	Self-contained 200 images without mask	100(Acc.)
Akram *et al*. (2022)	MobileNetV2	SMFD and RMFD datasets	100(Acc.)
	InceptionV3		96.5(Acc.)
	ResNe50V2		99.7(Acc.)
	VGG16		98.1(Acc.)
	DenseNet121		99.7(Acc.)
Aryal *et al*. (2019)	Deep learning CNN	Self-contained: 48 distinct sets of staff images, each featuring 15-20 pictures per individual without a mask	96(Acc.)
Aryal *et al*. (2019)	CNN	Self-contained 400 images without mask	96.15(Acc.)
Fu *et al*. (2017)	MTCNN	CASIA-web face	99.81(Acc.)
	ResNe-101	CACD2000	
		UMD face	
Hussain *et al*. (2021)	VGG-16	149,806 images	98.87(Acc.)
	MobileNetV2		99.60(Acc.)
	InceptionV3		99.40(Acc.)
	ResNet50		99.20(Acc.)
Sertic *et al*. (2022)	VGG16	1915 pictures of faces with masks and	98.70(Acc.)
	ResNet50V2	1928 pictures of faces without masks	99.00(Acc.)
Sethi *et al*. (2021)	MobileNet	45,000 images face data hybrid | Kaggle	82.30(Acc.)
	ResNet		93.40(Acc.)
	ResNet50		98.92(Acc.)
Ennouni *et al*. (2021)	VGG16	Plant Village (PV)	92.00(Acc.)
	Alex Net		95.00(Acc.)
	InceptioV3		91.00(Acc.)
	CNN		95.00(Acc.)
	MobileNet		95.00(Acc.)

Alhanaee *et al*. (2021) utilized three pre-trained networks, namely Alex Net, google net and squeeze net, in the development of the face recognition smart attendance system. Their findings indicated that the Alex net model achieved the highest validation accuracy, making it the optimal choice for data training.

Fu *et al*. (2017) used a convolutional neural network with res net-101 layers to train a dataset of almost 65 million samples for recording classroom attendance. Their results showed that a face recognition model could achieve an accuracy level of 98.87%.

A network architecture was used on the 1376 faces dataset with two classes of images for face mask detection. Modified models such as MobileNetV2 and VGG19 were used for face mask classification and obtained an accuracy of 95.08 and 91.3% for MobileNetV2 and VGG19, respectively (Oumina *et al*., 2020). Employed pre-trained models, including squeeze net, google net, AlexNet, ResNet50, VGG-16, and MobileNetV2, for masked face human identification. Remarkably, these six models demonstrated validation accuracy ranging from 97.8-100% when tested on datasets comprising 400 RGB images (Shatnawi *et al*., 2022). Furthermore, a mask classification model was developed using the mobilenetV2 framework through deep transfer learning, achieving an accuracy of 97.01% on the validation data, 98% on the training data, and 97.45% on the testing data. The dataset included 3771 images labeled "masked" and "unmasked," with 3743 images (Gupta *et al*., 2022). Furthermore, Shaheed *et al*. (2022) presented a pre-trained Xception model that employed a depth-wise separable convolutional neural network for the recognition of finger veins, which achieved an accuracy of 99% on SDUMLA and 90% on THU-FVFDT2 datasets. Finally, Mar-Cupido *et al*. (2022) utilized four pre-trained deep transfer learning models MobileNetV2, ResNet101V2, and ResNet152V2 to categorize images based on the style of face masks worn by individuals, such as KN95, N95, surgical and cloth masks. The method obtained an accuracy of 97.37, 98, 93.24 and 93.24% for ResNet152V2, ResNet101V2, MobileNetV2 and MobileNet, respectively.

The methodologies employed across the studies in Table 1 reflect a diverse range of approaches in the domain of image detection. Researchers have leveraged various deep learning architectures to address the challenge of identifying images. The studies incorporate a variety of pre-trained models such as VGG, AlexNet, MobileNet, Inception, ResNet, and DenseNet, showcasing the diversity in the selection of architectures. Convolutional Neural Networks (CNNs) are a prevalent choice, emphasizing their effectiveness in image-related tasks. The studies deploy CNNs to capture intricate features and patterns for accurate image detection. Additionally, some studies opt for a combination of multiple models, indicating a hybrid approach to image detection. This approach aims to harness the strengths of different architectures for improved accuracy.

Materials and Methods

Data Augmentation

Data augmentation is a method employed to address the limitation of a small sample size. It involves generating new and representative data from existing data, artificially increasing the size of the training dataset. This is accomplished by creating modified versions of the available training images, resulting in a significant improvement in the model's performance during the training process.

Dataset

We used the unmasked pins face recognition dataset (Kaggle, 2022), which consists of 17,534 cropped images of 105 celebrities collected from Pinterest. Each category within this dataset contains approximately 160 images for each individual. Exemplary facial images from this collection of celebrities are illustrated in Fig. 3.

During the data collection phase, we also included images of women wearing scarves to ensure cultural diversity. These images were collected from Pinterest and divided into five separate classes. Sample images of women wearing scarves can be seen in Fig. 2.

To transform the unmasked pins face recognition dataset into a masked-face dataset, we employed the MaskTheFace tool (Anwar and Raychowdhury, 2020). This approach integrates user-selected masks into each image, taking into account factors such as the face's orientation, mask compatibility, and lighting conditions Illustrative of this process is provided in Fig. 4.

Moreover, MaskTheFace is a computer vision script designed for concealing faces within images. It employs a face landmarks detector rooted in Dlib to determine the tilt of the face, which guides the selection of an appropriate mask template from a collection of masks. This template mask is subsequently adjusted to align precisely with the contours of the face. The block diagram of the process can be seen in Fig. 5.

To improve the efficiency of our pre-trained models, we employed data augmentation techniques to increase the volume of the training dataset, reduce overfitting, and enhance the models' ability to generalize. After performing data augmentation on our datasets, the number of samples increased to 138,765. Our augmented dataset comprises 110 different classes, each with an average of 1,262 images per subject. It is important to note that the faces of the students in our study are part of this augmented dataset.

Fig. 2: Sample women with scarf

Fig. 3: Sample images from the pins face recognition dataset

Fig. 4: Masked faced dataset

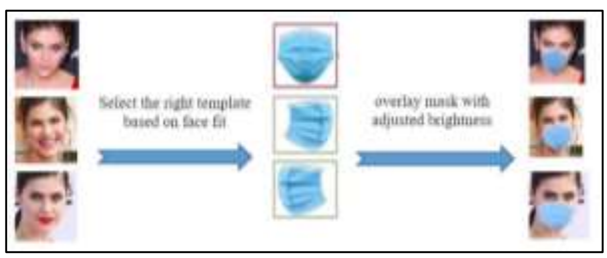

Fig. 5: Block diagram

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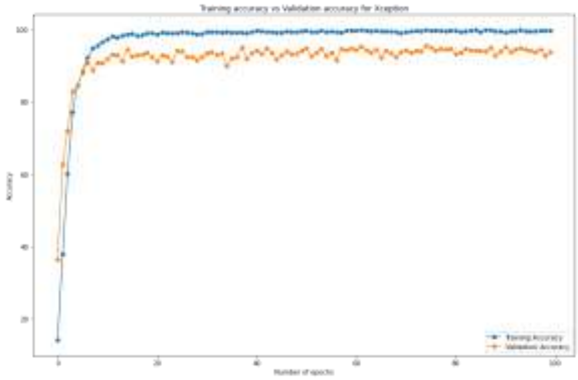
Results and Discussion

Experimental Setup

The experiments were conducted on Colab Pro notebooks with 25GB RAM, and a computer fitted with an Intel® CoreTM) i5 CPU M520 @ 2.40GHz (4 CPUs), ~2.4GHz, with 8GB RAM and an integrated Python 3.8 kernel for developing various deep learning models. We implemented our project using Python, utilizing various open-source libraries for data manipulation, including pandas and NumPy. Additionally, we used Matplotlib for data visualization. We utilized scikit-learn, TensorFlow, and Keras for training our transfer learning models

Results Based on Pre-Trained Models

A total of one hundred epochs were used to train the Xception network. Based on the average time of 120 sec for each epoch, Fig. 6 displays a validation accuracy of 96.75%.



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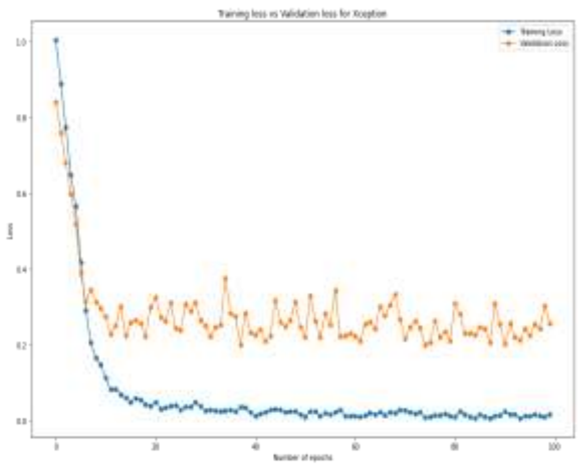
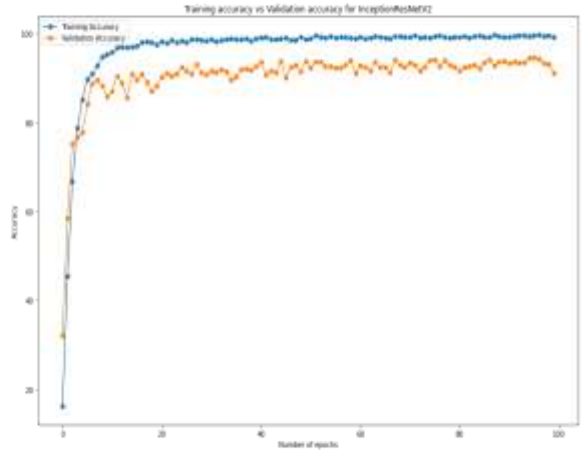


(b)

Fig. 6: Performance evaluation of the Xception model; (a) Display the accuracy comparison between training and validation; (b) Illustrate the loss comparison between training and validation



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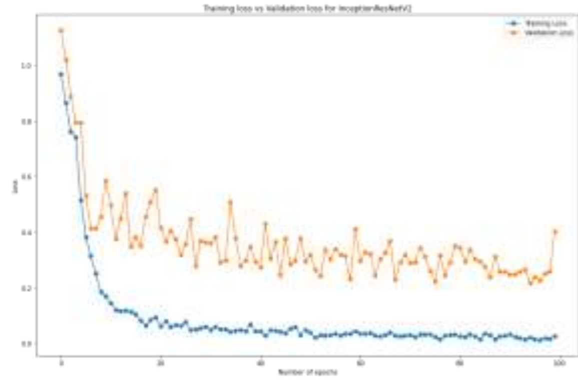

(b)

Fig. 7: Performance evaluation of InceptionResNetV2 model; (a) Display the accuracy comparison between training and validation; (b) Illustrate the loss comparison between training and validation

The InceptionResNetV2 model was trained over the course of 100 epochs, with an average epoch duration of 105 sec. Figure 7, the model's validation accuracy during this training phase was 96.50%.

Training of the DenseNet201 network involved 100 epochs in total, with an average epoch length of 69 sec. Figure 8, this training effort produced a validation accuracy of 95.28%.

Training the ResNet101V2 network required 100 epochs in total. Each epoch took an average of 76 sec, and it achieved a validation accuracy of 90.94%, as illustrated in Fig. 9.

The MobileNetV2 network required a total of 100 epochs to train. Figure 10, the validation accuracy was 88.60% with an average epoch period of 45 sec.

Training of the EfficientNetB0 network took place over 100 epochs in total. As illustrated in Fig. 11, each epoch had an average duration of 45 sec and achieved a validation accuracy of 88.70%.

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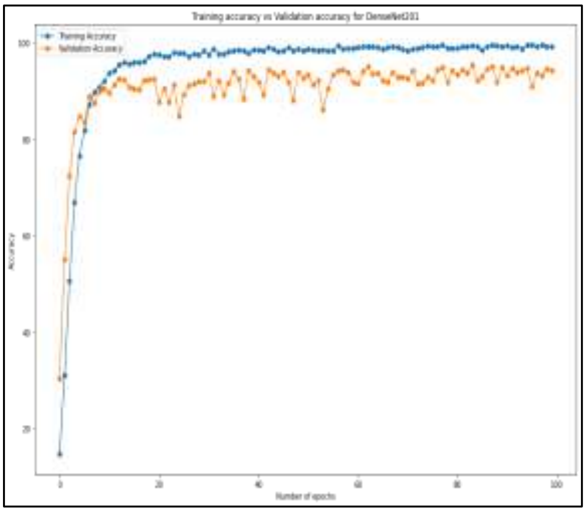

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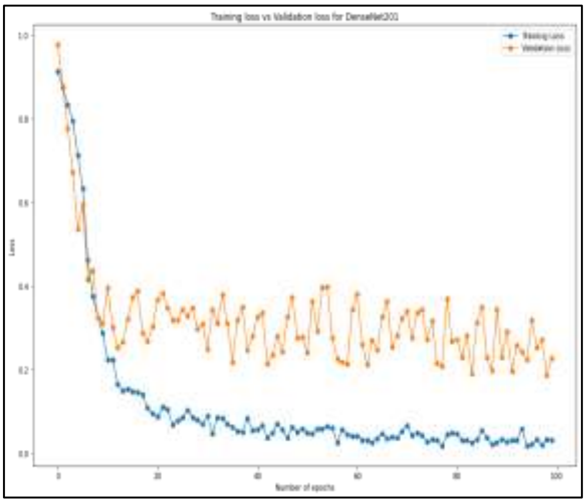
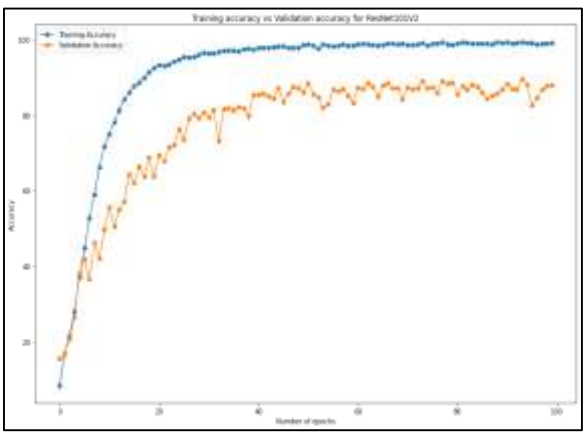


(b)

Fig. 8: Performance evaluation of DenseNet201 model; (a) Display the accuracy comparison between training and validation; (b) Illustrate the loss comparison between training and validation



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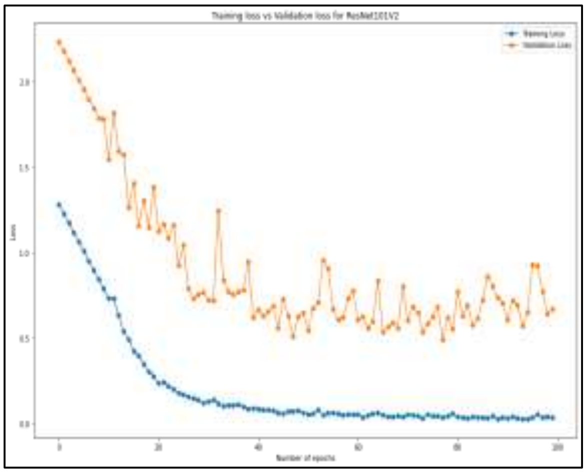
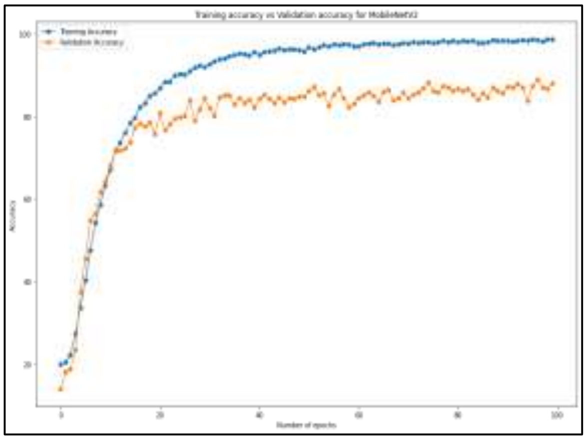


(b)

Fig. 9: Performance evaluation of ResNet101V2 model; (a) Display the accuracy comparison between training and validation; (b) Illustrate the loss comparison between training and validation



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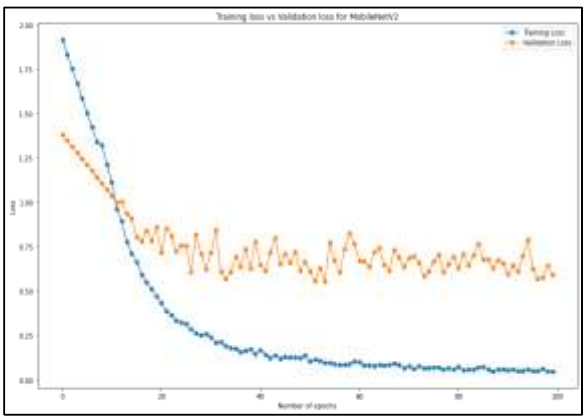

(b)

Fig. 10: Performance evaluation of MobileNetV2 model; (a) Display the accuracy comparison between training and validation; (b) Illustrate the loss comparison between training and validation

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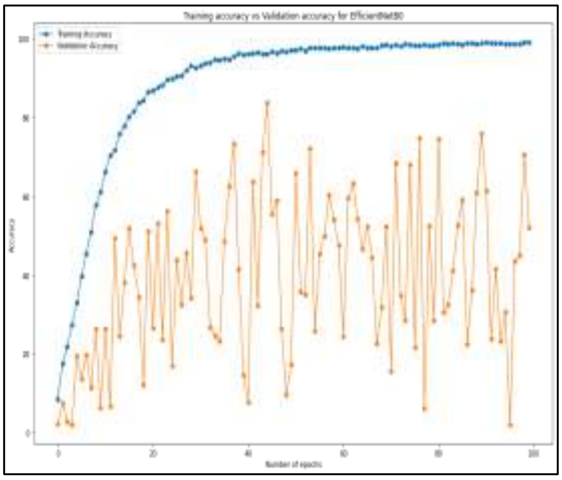

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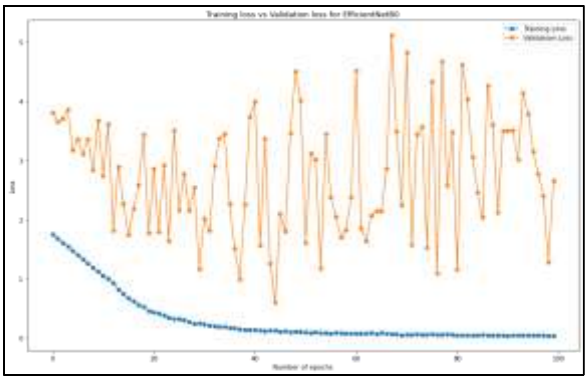
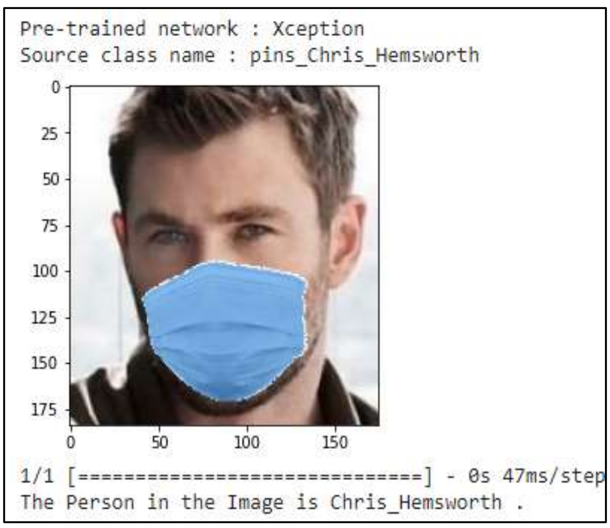


(b)

Fig. 11: Performance evaluation of EfficientNetB0 model; (a) Display the accuracy comparison between training and validation; (b) Illustrate the loss comparison between training and validation.



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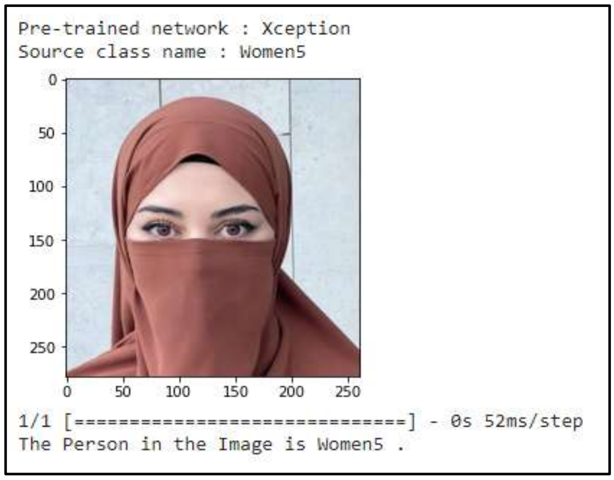

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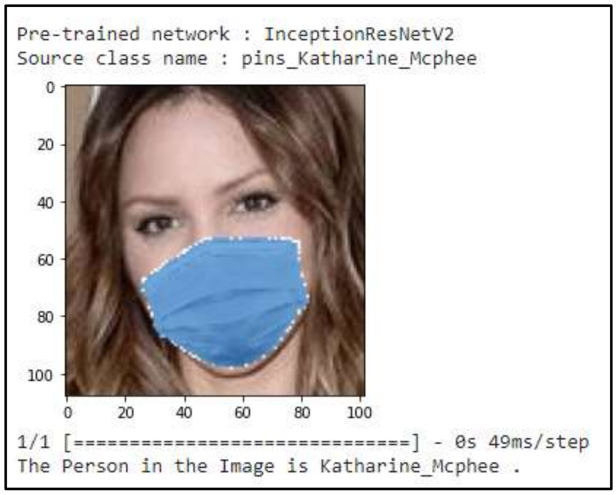

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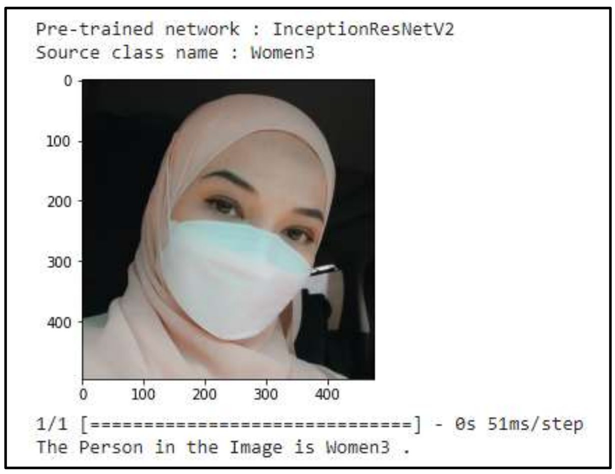

(d)

Fig. 12: Testing results with Xception and InceptionResNetV2

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Table 2: Comparison of CNN training performance

Model	Epochs	Validation accuracy %	Hardware resource
Xception	100	96.75	GPU
InceptionresNetV2	100	96.50	GPU
MobileNetv2	100	88.60	GPU
DenseNet201	100	95.28	GPU
ResNet101V2	100	90.94	GPU
EfficientNetB0	100	88.70	GPU

The results of the test predictions for the pre-trained models, including Xception and InceptionResNetV2, are depicted in Fig. 12a-b illustrate the performance of the Xception model, which emerges as the top-performing model, achieving the highest probability of 100% for predicting a person's name corresponding to the actual label. Fig. 12c-d illustrate the performance of the InceptionResNetV2 model, which exhibits notable accuracy, achieving a probability of 100% for predicting a person's name corresponding to the actual label.

Table 2 presents a comparison of the training performance of various Convolutional Neural Network (CNN) models. The models are evaluated based on three key metrics: The number of training epochs, validation accuracy, and the hardware resource used during training. For the 'Epochs' metric, all models were trained for 100 epochs. In the 'Validation Accuracy' metric, Xception achieved the highest validation accuracy at 96.75%, closely followed by InceptionResNetV2 at 96.50%, and DenseNet201 at 95.28%. EfficientNetB0 and MobileNetV2 had relatively lower validation accuracies at 88.70 and 88.60%, respectively. These accuracy values provide insights into the models' ability to generalize well to unseen data. Finally, for the 'Hardware Resource' metric, all models were trained using a GPU, indicating a parallel processing capability that significantly accelerates training compared to traditional CPU-based training. The use of GPUs is common in deep learning tasks due to their ability to handle the computational demands of neural network training efficiently.

Xception and InceptionResNetV2 demonstrated superior validation accuracies, suggesting their effectiveness in capturing complex patterns in the dataset. DenseNet201 also performed well, indicating the effectiveness of densely connected convolutional architectures. However, MobileNetV2 and EfficientNetB0 achieved comparatively lower accuracies, suggesting potential trade-offs between model complexity and accuracy. These findings highlight the effectiveness of the Xception and InceptionResNetV2 models in the detection and identification of students' faces.

The deep transfer learning approach adopted in the study is particularly valuable during the COVID-19 pandemic, where conventional attendance systems may face disruptions. The advanced models and methodologies employed demonstrate adaptability to challenging conditions and disruptions in the educational environment.

Given the context of the COVID-19 pandemic, the study's outcomes contribute to the development of attendance systems that are resilient to disruptions caused by public health emergencies. This is essential for maintaining continuity in education despite unforeseen challenges.

In this comparative analysis of the outcomes, we have scrutinized this research alongside relevant preceding studies. The work of Akram *et al*. (2022), Hussain *et al*. (2021), Sertic *et al*. (2022), and Sethi *et al*. (2021) has established the effectiveness of employing deep transfer learning, specifically utilizing models such as MobileNet V2, InceptionV3, ResNe50V2, and DenseNet201, for tasks related to the classification of face masks. Our methodology extends beyond this groundwork. We applied the deep transfer learning technique to identify faces and log student attendance during classroom learning sessions, considering the repercussions of the COVID-19 pandemic. This illustrates that deep transfer learning makes the model adaptable to diverse situations involving students wearing masks, enhancing its capability to accurately discern faces. This aligns with the insights of Zhuang *et al*. (2020), who emphasized the significance of employing transfer learning methods for various computer vision assignments, including image classification.

Conclusion

In this study, we suggest a deep transfer learning method for a COVID-19 pandemic student attendance system. We utilized a computer vision technique called MaskTheFace to convert our face dataset into a masked face dataset. Six pre-trained convolutional neural networks were employed for masked face identification on this dataset.

To ensure cultural inclusivity, we integrated five classes for women wearing scarves in our dataset. The datasets were then subjected to data augmentation techniques, which increased the size of the training samples and produced 138,765 facial images.

The six pre-trained networks used in this study were Xception, inception ResNetV2, MobileNetV2, DenseNet, ResNet101V2, and efficient NetB0, which achieved validation accuracies of 96.75, 96.50, 88.60, 95.28, 90.94 and 88.70%, respectively.

For future work, the main goal is to implement this approach in real-world applications to create an intelligent student attendance system integrating a pertained model of high prediction accuracy. Such a system would be able to control attendance in an educational center based on the use of face detection and facial recognition technology during the COVID-19 pandemic.

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Author's Contributions

Slimane Ennajar: Participated in all the experiments, including data collection and analysis, coding, and building all the pre-trained models. They also evaluated the results and made significant contributions to the writing of the manuscript.

Walid Bouarifi: Provided essential guidance and oversight throughout the project. They reviewed and approved all research activities, ensuring that the project adhered to the highest standards of academic rigor. Additionally, they managed the administrative aspects of the project, including supervising and scheduling.

Ethics

The current study is an original research endeavor, and the lead author attests that all co-authors have reviewed and endorsed the manuscript without any ethical concerns.

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