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Protective face covering: An application of MobileNetV2 detector

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ABSTRACT

COVID-19 has created a global serious health hazard with far-reaching consequences for society, our perceptions of the world, and how we live our daily lives. As a result, the World Health Organization recommended the use of face masks and social isolation to help reduce the rising number of infections. However, subsequent research has revealed that face masks alone can be ineffective, particularly in crowded settings or hospitals. Face shields can also be used in addition or as an alternative for face masks because they are indefinitely reusable and can be washed with soap and water or standard disinfectants. Because most detectors for fighting COVID-19 only focus on the face mask alone, we proposed a transfer learning model by fine-tuning the pre-trained MobilenetV2 architecture, to detect, recognize, and distinguish faces with shield, mask, and those without either. This study applied a standard image recognition pipeline, which is comparable to that used by most traditional recognition programs. In doing this, we first downloaded and scrapped images from search engines to form our dataset, we then pre-processed the images by the application of image augmentation to address the limited availability of the dataset for a better training and validation. After which a multi-class detection system was accomplished. The results of the study achieved 98 percent accuracy on the validated dataset. It is therefore recommended that this model can be improved to capture all forms of face covering and be integrated into CCTV cameras for its detection in important places like hospitals.

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INTRODUCTION

The rise of coronavirus disease in 2019 has sparked a global health catastrophe that has had a significant impact on humanity's perception of the environment and our everyday lives (Wang et al., 2020). A new severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) outbreak was discovered in Wuhan, China, in December 2019. After the disease infected 7,711 people in China and resulted in 170 confirmed fatalities, the World Health Organization designated it a pandemic and named it COVID-19 (WHO, 2020). As of December 2020, the COVID-19 outbreak had infected over 75,039,853 people in more than 200 nations throughout the world, resulting in over 1,600,659 deaths, with a fatality rate of around 37% (WHO, 2020), and shutting down major economic activities (Geroso & Aloba, 2021).

The novel coronavirus has resulted in person-to-person transmission and also the transmission can be from an asymptomatic carrier with no symptoms. The bulk of positive cases are found in densely populated areas. As a result, scientists recommended wearing a mask in public places to avoid disease transmission and maintaining a social buffer of at least 2 meters between individuals to prevent person-to-person transmission (Feng et al., 2020). Prior to COVID-19, only a few people wore masks to protect their health from air pollution, and health professionals wore masks while practicing at hospitals (Matrajt & Leung, 2020).

COVID-19 must be controlled at source to prevent a sustaining surge in confirmed cases and death cases. SARS-CoV-2, which is known to be transmissible from presymptomatic and asymptomatic individuals, can be transmitted by small respiratory droplets (Howard et al., 2021). The use of face masks, as advised by the WHO, has gained widespread support because it can prevent the spread of potential viruses during a pandemic (Chen et al., 2020). Recent studies have shown that using a face mask alone is not completely effective, especially in crowded places or hospitals (Mundell, 2020). The use of face masks without other adequate Personal Protective Equipment (PPE) has resulted in an early surge in COVID-19, resulting in the deaths of 570,000 health workers (Pan American Health Organization [PAHO], 2020). Now a team of experts believes face shields might replace masks as a more comfortable and more effective deterrent to COVID-19 (Mundell, 2020). According to Perencevich (2020), face shields can be used as an alternative to face masks because they are infinitely reusable and can be cleaned with soap and water or common disinfectants. Face shields are typically more comfortable to wear than masks, and they create a barrier that prevents people from accidentally touching their own faces (Mundell, 2020). Face Shields have been shown to reduce immediate viral exposure by 96 percent in a simulation study by an Iowa team, but they recommended that face shields should only be one component of all infection control efforts along with social distancing and hand washing (Mundell, 2020). In a situation where a person cannot avoid crowded places, or when a healthcare worker is in a hospital with many COVID-19 patients, face shield can also present an alternative option.

Policymakers are facing a lot of challenges and risks in containing the spread and transmission of COVID-19. Even though the rules and laws of social distancing and wearing of masks are in place, the process of monitoring large groups of people is difficult (Matrajt & Leung, 2020). This made the use of machine learning and deep learning by experts to fight the pandemic in many ways. Machine learning allows researchers and medical workers to evaluate a vast array of data to forecast the distribution of COVID-19, serve as an early warning mechanism for potential pandemics, and classify potential diseases (Chowdary et al., 2020).

Since some human beings may not totally abide by social distancing protocol, especially in a hospital, Artificial Intelligence (AI) experts have designed face mask detectors to safeguard people and society in general by detecting erring individuals who decide not to wear them. The problem with these detectors is that they only consider those wearing the face mask alone. Even with the advantages the face shield has over the face mask, people wearing the face shield will still be considered as erring individuals because the system was not designed to take the face shield into consideration. For example, a system designed in an organization to open doors to only those wearing facemasks will not open doors to those wearing face shields because the system might consider them to be violating the organizations' rules, where as a human security guard will let them in because he understands that face shields can also protect people against COVID-19. It is therefore pertinent to design a model that will also be able to detect face shield users and consider them not dangerous, so that they can have the full benefits of those wearing a facemask. This study put the face shield into consideration by designing a model using transfer learning for the detection of both face shield and face mask. The proposed model can be integrated with surveillance cameras in hospitals, long-term meetings where wearing a face mask can be uncomfortable, and other crowded places to impede COVID-19 transmission by detecting people who are not wearing either a face shield or mask.

Objectives

The general objective of this research is to build a deep learning model that will be able to detect face masks as well as face shields with the help of transfer learning using computer vision. To be able to carry out this research, the specific objectives that were followed are listed below:

1. Create our dataset by scrapping facial images from image search engines of people wearing face masks, face shields, and those not wearing any of the two.
2. Perform image augmentation on the dataset.
3. Apply transfer learning and fine tune MobileNetV2 architecture for classification.
4. Evaluate the performance of the classification.

LITERATURE REVIEW

Machine learning evolved from computer science, which focuses on the development of algorithms that can learn from experience. To learn, they require data with specific attributes, which the algorithms use to try and find meaningful predictive patterns. According to Ahmed (2018), machine learning (ML) problems can be divided into three categories: supervised, unsupervised, and reinforcement. In supervised learning, a human expert conducts some experiments in a restricted environment and notices their results. The supervised learning algorithm explores input data collected from experiments and maps them into outputs.

Deep learning is a subfield of machine learning, which is, in turn, a subfield of AI (Goodfellow et al., 2016). For a graphical depiction of this relationship, please refer to Figure 1. The central goal of AI is to provide a set of algorithms and techniques that can be used to solve problems that humans perform intuitively and nearly automatically, but that are otherwise very challenging for computers (Rosebrock, 2017). A great example of such a class of AI problems is interpreting and understanding the contents of an image. This task is something that a human can do with little-to-no effort, but it has proven to be extremely difficult for machines to accomplish. While AI embodies a large, diverse set of tasks related to automatic machine reasoning (inference, planning, heuristics, etc.), the machine learning subfield tends to be specifically interested in pattern recognition and learning from data (Ahmed, 2018). Rosebrock (2017) explains that artificial neural networks (ANNs) are a class of machine learning algorithms that learn from data and specialize in pattern recognition. They are inspired by the structure and function of the brain. Deep learning belongs to the family of ANNs, and in most cases, the two terms can be used interchangeably.

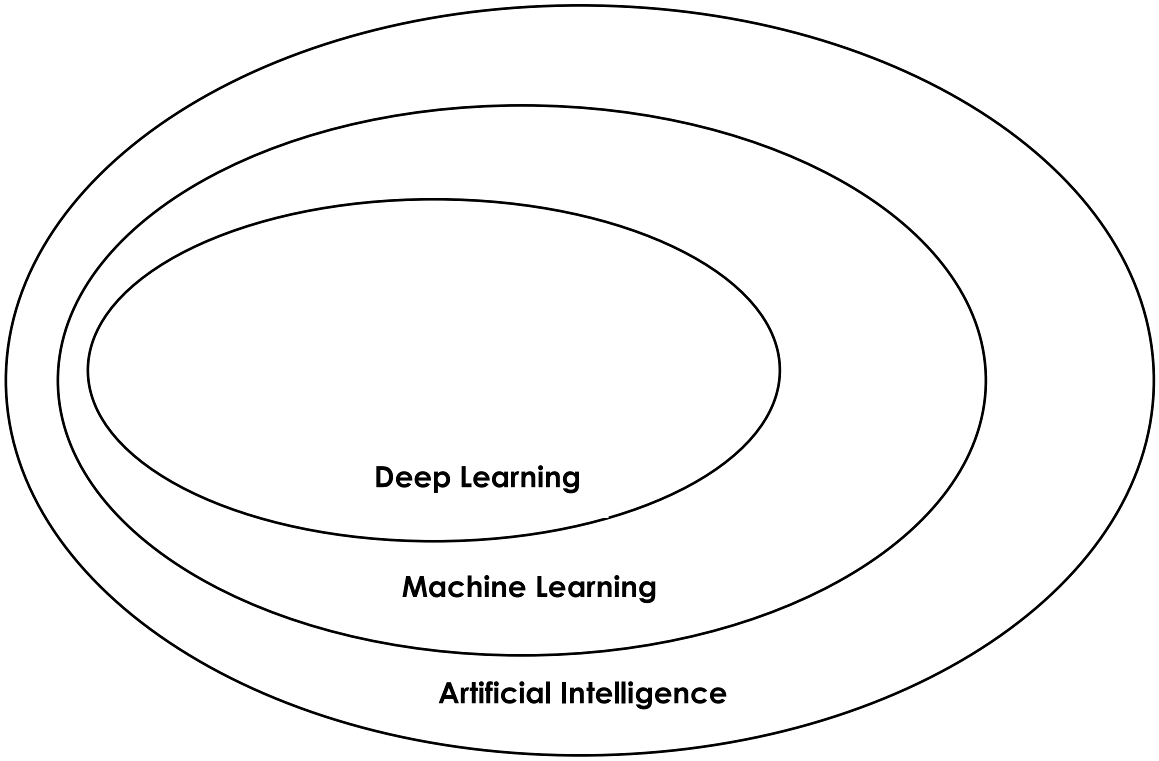

Figure 1. Diagram depicting Deep Learning as sub-field of Machine Leaning. (Goodfellow et al., 2016)

Deep learning networks consume a lot of resources and are computationally expensive. Unlike traditional machine learning models, they have millions of parameters and thus require a large amount of training data to avoid overfitting (Marketting, 2019). ImageNet, for example, has over 14 million hand-labeled images in its database for image recognition. However, obtaining a large labeled dataset to work with is not always possible, and gathering the dataset manually can be a tedious and time-consuming task. The use of transfer learning is one of the possible solutions to the aforementioned problem (Sangha, 2020).

Humans are born with the ability to transfer knowledge from one task to the next. What we learn as knowledge while learning about one task, we apply to other tasks as well. As a result, transfer learning is defined as a machine learning method in which we use a previously trained model as a starting point to develop another model for a similar task (Sangha, 2020). The goal of transfer learning is to extract knowledge from one or more source tasks, such as ImageNet tasks, and apply it to a target task. A variety of AI techniques such as ML and DL can be used in a variety of ways to prevent the spread of COVID-19 (Agarwal, 2019). ML and DL techniques can forecast the spread of COVID-19 and help to design an early prediction system that can aid in disease monitoring. Emerging technologies such as the Internet of Things (IoT), AI, big data, DL, and ML are being used for the early prediction and diagnosis of complex diseases such as COVID-19 (Ting et al., 2020; Sonbhadra et al., 2020; Al-Mamun & Kabir, 2021). Most of the literature accessed focused on face mask detection, but the main aim of this work is to design a model that can also identify people who are wearing face shields, apart from those wearing facemasks, which, if deployed correctly, could help ensure safety in the world we live in.

Ejaz et al. (2019) used Principal Component Analysis to implement a traditional machine learning method for recognizing masked and unmasked faces. The findings showed that extracting features from a masked face is more difficult than extracting features from an unmasked face. They discovered that wearing masks affects the accuracy of mask face classification using PCA. The paper concluded that a face without a mask performs better in PCA, as wearing a mask reduces accuracy by 70%. Ud Din et al. (2020) proposed a novel GAN-based network for removing mask objects from facial images. The GAN employed two discriminators: the first extracts the masked face's global structure, and the second extracts the missing region from the masked face. They used paired synthetic datasets in the training process. The introduced model yielded high-quality results for removing masks from the face. Qin and Li (2020) developed a face mask recognition system based on the SRCNet classification network that classified pictures into three categories with an accuracy of 98.7%: "correct facemask wearing," "incorrect facemask wearing," and "no facemask wearing." Loey et al. (2020) proposed a novel deep learning model for surgical face mask detection based on ResNet-50 and YOLO-v2. The proposed model is made up of two parts. The first part is intended for feature extraction using the ResNet-50 deep transfer learning model. The second part is based on YOLO v2, which is intended for the detection of surgical face masks. Two datasets of surgical face masks were combined into a single dataset for the study. The investigation's findings showed that Adam optimizer achieved the highest average precision percentage of 81% as a detector. Loey et al. (2020) went on to propose a face mask classification model that combines deep transfer learning with machine learning methods. The proposed model had two stages. 1. Feature extraction using ResNet50. 2. Support Vector Machines, decision trees, and ensemble-based classification. To evaluate the proposed methodology, three datasets were used as benchmarks, and the SVM classifier had the highest accuracy of 99.64%. Chowdary et al. (2020) also used the transfer learning model to automatically recognize people who might not wear a mask. The model was created by fine-tuning a cutting-edge deep learning model called inceptionV3, which was trained and tested on a Simulated Masked Face Dataset (SMFD). During testing, the result achieved a precision of 100%.

Since masks have such a limited service life and are used all over the world, special machines for centralized detection are not practical. As a result, it is critical to develop an easy-to-use, portable testing system capable of detecting masks at any time and from any place. In most cases, face masks are used in high frequency but in a short-term manner. In order to solve this problem of not knowing which stage of the mask belongs to, Chen et al. (2020) proposed a cell phone-based detection method. In this method, four features were extracted from the GLCMs of the micro-photos of the face mask. Then the KNN algorithm was used to implement a three-result detection scheme. According to the results of validation experiments, the device can achieve a precision of 82.87% 8.50% on the testing dataset. Another research by Ristea and Ionescu (2020) proposed a mask detection system by using speech. The findings can be used to model speech in forensic investigations, interaction between surgeons, or people protecting themselves against contagious diseases like COVID-19. It uses data augmentation by cycle-consistent GANs to improve mask detection. This model surpassed the baseline approach by 2.8% and provided a performance boost of 0.9% on a private test. As previously stated, all previous research has been based on detecting whether an individual is wearing a face mask or not by employing various machine and deep learning techniques. To the best of our knowledge, no previous work has considered face shield detection, despite the fact that it has advantages over face masks. This makes facemask detectors consider people wearing face shields as dangerous as those not having face coverings. As a result, this study employs the MobileNetV2 architecture with pre-trained ImageNet weights to detect the use of face shields, facemasks, and individuals who do not have face covering.

METHODS

The study methodology followed a standard image recognition pipeline similar to most traditional recognition applications. This methodology has predefined steps to be followed to achieve the desired result.

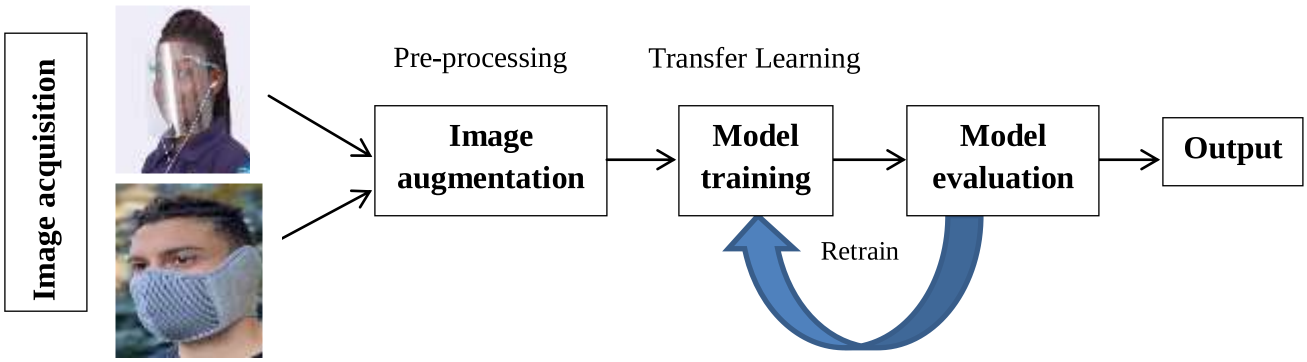

Figure 2. Proposed Methodology

Image acquisition

This step deals with how the data was collected and sourced. For this model, the primary source of image data was collected by scraping images from a web browser for faces with shields and masks. We acquired 1655 images, belonging to three classes. As shown in figures 3, 4 and 5, 600 images were for facial images without a face shield or mask. 455 were images with a face shield, while the remaining 600 were for images with a face mask. The captured images serve as inputs for the model.

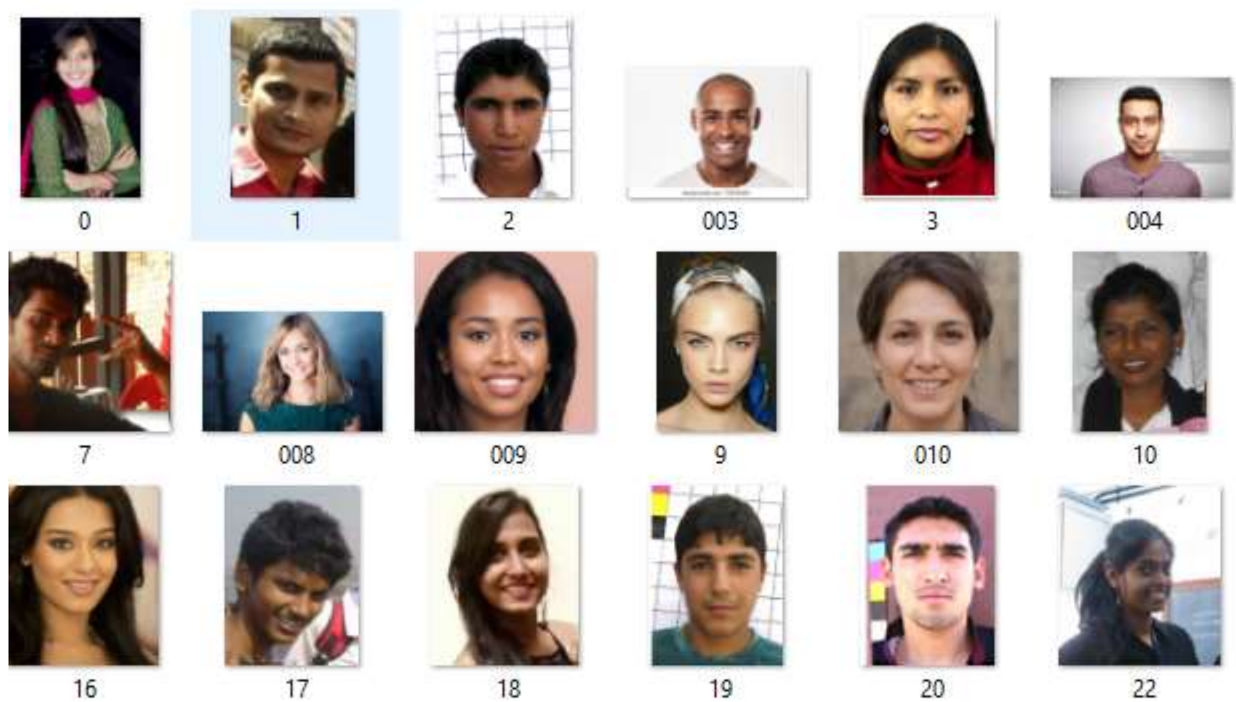

Figure 3. Normal Facial Images. (Bhandary, 2020)

Figure 4. Face Mask images. (shutterstock, n.d.)

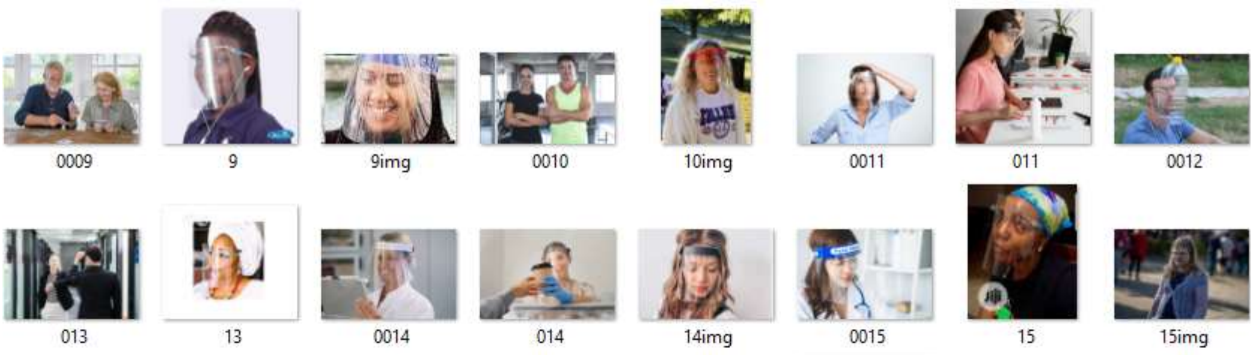

Figure 5: Images with Face Shield. (iStock, n.d.)

Image augmentation

Image augmentation is a preprocessing method that is used by artificially manipulating images in a dataset to increase the size of the training dataset (Chowdary et al., 2020). In this work, eight different operations were performed, namely shearing, contrasting, horizontally flipping, spinning, zooming, and blurring, were applied to the training images. The dataset generated is then resized to 224 x 224 pixels and converted to array format, and scaling the pixel intensities to the range [-1, 1] in the input image (via the convenience preprocess input function).

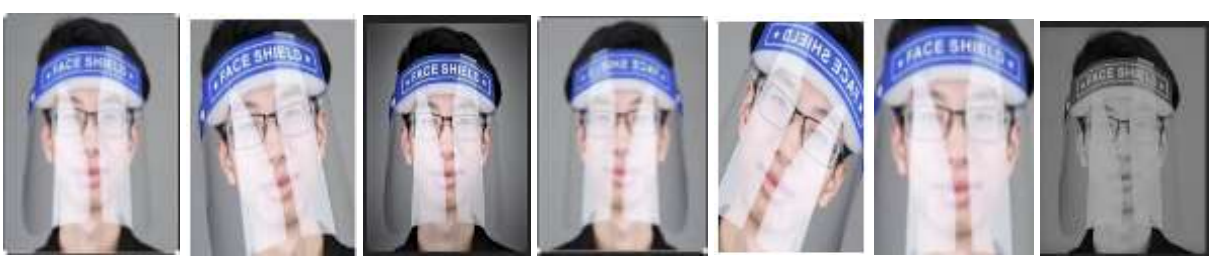

Figure 6. Augmented Image on Annotated data from iStock (n.d.)

Model training

Deep neural networks are used for image classification because of their better performance than other algorithms (Chowdary et al., 2020). But training a deep neural network is costly and time-consuming because it necessitates a large amount of computing power and other resources (Marketting, 2019). Deep learning-based transfer learning is being developed in order to make the network train faster and more cost-effective. Transfer learning enables the neural network's learned information in terms of parametric weights to be transferred to the new model (Sangha, 2020). Even when trained on a small dataset, transfer learning improves the efficiency of the new model. Several pre-trained models, such as InceptionV3, Xception, MobileNet, MobileNetV2, VGG16, ResNet50, and others, have been trained using 14 million images from the ImageNet dataset (Chowdary et al., 2020). We used Keras and TensorFlow to train a classifier to automatically detect whether a person is wearing a face shield, face mask, or not. We accomplished this task by fine-tuning the MobileNetV2 architecture, an extremely effective architecture that could be applied to embedded devices with limited computational power (for example, Raspberry Pi, Google Coral, NVIDIA Jetson Nano, and so on) (Rosebrock, 2020). This is because deploying our face shield detector to embedded devices could lower the cost of manufacturing such detection systems. Also, the ability to run deep networks on personal mobile devices enhances the user experience by providing access at any time, as well as additional benefits for protection, privacy, and energy consumption, which is why we used this architecture.

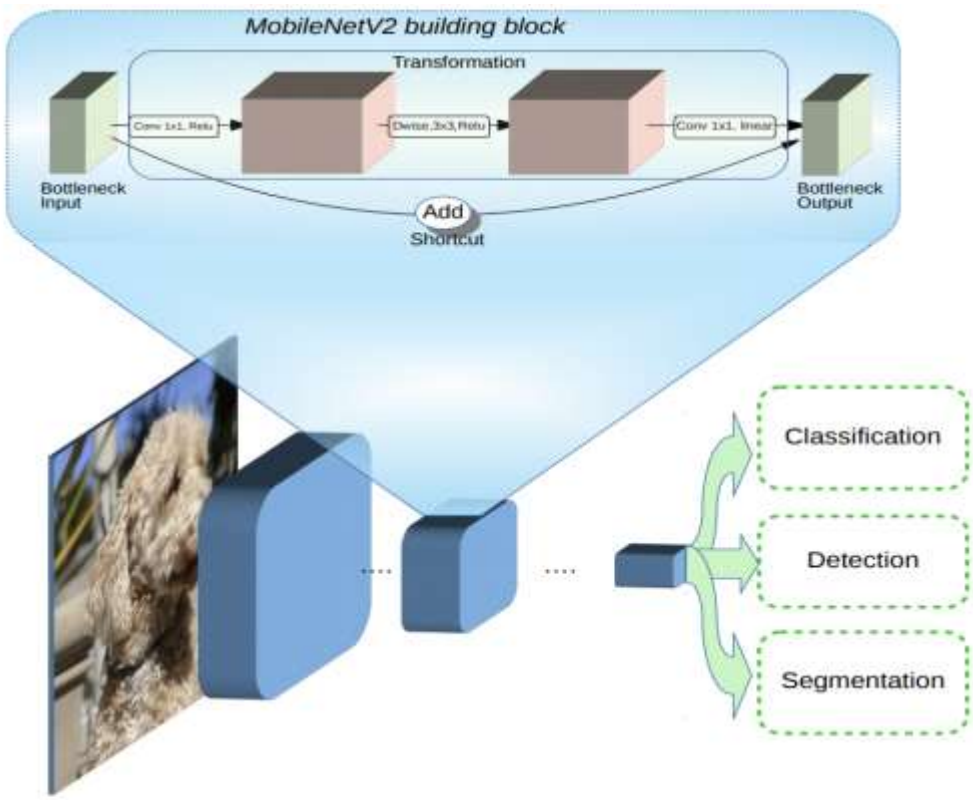

Figure 7. Overview of MobileNetV2 Architecture. Sandler et al. (2018).

For this work, fine-tuning is the strategy we used to establish a baseline model while saving a considerable amount of time. Fine-tuning setup is a three-step process. We first load MobileNetV2 with pre-trained ImageNet weights, leaving off the head of the network. Then we build a new fully connected head and attach it to the base in place of the old one, and freeze the base layers of the network. The weights of these base layers will not be updated during the backpropagation process, while the weights of the head layer will be tuned. In order to train the model, we set hyperparameter constants that include the initial learning rate of 1e-4, the number of training epochs to 20 epochs, and the batch size to 32. The dataset was also segmented into 80% for training and 20% for validation before the training occurred. Once training is complete, we evaluated the resulting model on the validation set.

Model evaluation

Model evaluation is the process of assessing how well a model performs against real data. This specifically applies the model to test the data in determining if the model, based on a training set, can be applied to other data. In particular, it helps eliminate the over-fitting phenomenon that can occur whenever the same data is used for both training and testing and matches the built data too well, but underperforms on other data (Ritchie, 2018). The model was validated on 20% of the data. The evaluation metrics used in this work include accuracy, precision, recall, and training and validation loss. Where the performance is low, the model was retrained until it shows minimal validation loss.

RESULTS AND DISCUSSION

A dataset of 1655 facial images was scraped from web images. 80%, which is equivalent to 1392 images, were used for training and three hundred and thirty one images were used for validation. The MobileNetV2 architecture with pre-trained ImageNet weights was fine-tuned in the conduct of the experiments. The input parameters were set equally to 224 pixels according to their input image width and height. The batch size during training was set to 32 images, and 20 iterations were set for the number of epochs with the initial learning rate set to 0.00001. The model was then compiled using Adam's optimizer, a learning rate decay schedule, and categorical cross-entropy was used to calculate its loss.

```
[INFO] compiling model...
[INFO] training head...
2021-12-25 12:22:20.330598: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:116] None of the MLIR optimization passes are enabled
Epoch 1/20
41/41 [==============================] - 68s 2s/step - loss: 1.2354 - accuracy: 0.4369 - val_loss: 0.4383 - val_accuracy: 0.8882
Epoch 2/20
41/41 [==============================] - 59s 1s/step - loss: 0.5329 - accuracy: 0.7960 - val_loss: 0.2398 - val_accuracy: 0.9607
Epoch 3/20
41/41 [==============================] - 61s 1s/step - loss: 0.3730 - accuracy: 0.8555 - val_loss: 0.1836 - val_accuracy: 0.9637
Epoch 4/20
41/41 [==============================] - 63s 2s/step - loss: 0.2471 - accuracy: 0.9105 - val_loss: 0.1364 - val_accuracy: 0.9668
Epoch 5/20
41/41 [==============================] - 63s 2s/step - loss: 0.2218 - accuracy: 0.9166 - val_loss: 0.1171 - val_accuracy: 0.9758
Epoch 6/20
41/41 [==============================] - 72s 2s/step - loss: 0.1805 - accuracy: 0.9384 - val_loss: 0.1042 - val_accuracy: 0.9758
Epoch 7/20
41/41 [==============================] - 66s 2s/step - loss: 0.1643 - accuracy: 0.9475 - val_loss: 0.1008 - val_accuracy: 0.9728
Epoch 8/20
41/41 [==============================] - 70s 2s/step - loss: 0.1701 - accuracy: 0.9353 - val_loss: 0.0803 - val_accuracy: 0.9849
Epoch 9/20
41/41 [==============================] - 65s 2s/step - loss: 0.1317 - accuracy: 0.9537 - val_loss: 0.0765 - val_accuracy: 0.9819
Epoch 10/20
41/41 [==============================] - 75s 2s/step - loss: 0.1127 - accuracy: 0.9622 - val_loss: 0.0726 - val_accuracy: 0.9758
Epoch 11/20
41/41 [==============================] - 70s 2s/step - loss: 0.1074 - accuracy: 0.9586 - val_loss: 0.0671 - val_accuracy: 0.9819
Epoch 12/20
41/41 [==============================] - 64s 2s/step - loss: 0.0992 - accuracy: 0.9690 - val_loss: 0.0649 - val_accuracy: 0.9819
Epoch 13/20
41/41 [==============================] - 63s 2s/step - loss: 0.0867 - accuracy: 0.9772 - val_loss: 0.0609 - val_accuracy: 0.9849
Epoch 14/20
41/41 [==============================] - 63s 2s/step - loss: 0.0963 - accuracy: 0.9710 - val_loss: 0.0614 - val_accuracy: 0.9819
Epoch 15/20
41/41 [==============================] - 67s 2s/step - loss: 0.1023 - accuracy: 0.9621 - val_loss: 0.0589 - val_accuracy: 0.9849
Epoch 16/20
41/41 [==============================] - 63s 2s/step - loss: 0.0771 - accuracy: 0.9746 - val_loss: 0.0629 - val_accuracy: 0.9758
Epoch 17/20
41/41 [==============================] - 65s 2s/step - loss: 0.0721 - accuracy: 0.9746 - val_loss: 0.0571 - val_accuracy: 0.9849
Epoch 18/20
41/41 [==============================] - 62s 2s/step - loss: 0.0679 - accuracy: 0.9832 - val_loss: 0.0553 - val_accuracy: 0.9819
Epoch 19/20
41/41 [==============================] - 61s 1s/step - loss: 0.0746 - accuracy: 0.9715 - val_loss: 0.0572 - val_accuracy: 0.9819
Epoch 20/20
41/41 [==============================] - 61s 1s/step - loss: 0.0718 - accuracy: 0.9772 - val_loss: 0.0553 - val_accuracy: 0.9819
[INFO] evaluating network...
```

Figure 8. Training Visualization of 20 Epochs

Figure 8 presents the visualization of the training over 20 epochs. It shows that during the training process, as can be seen from the figure, the model was able to learn from the pool of dataset provided with minimal over-fitting. This is because the training loss is similar to the validation loss. Hence, the model should be able to generalize when given a different image, as will be seen during implementation. Figure 9 shows a loss/accuracy graph over 20 epochs.

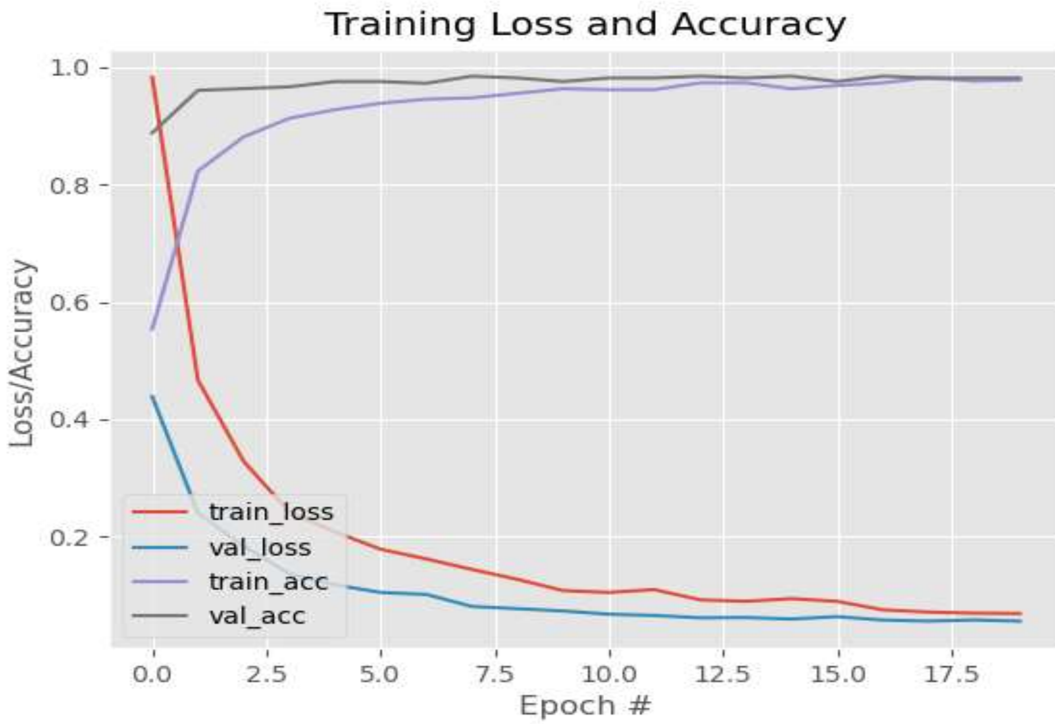

Figure 9. The Accuracy/Loss Performance Graph

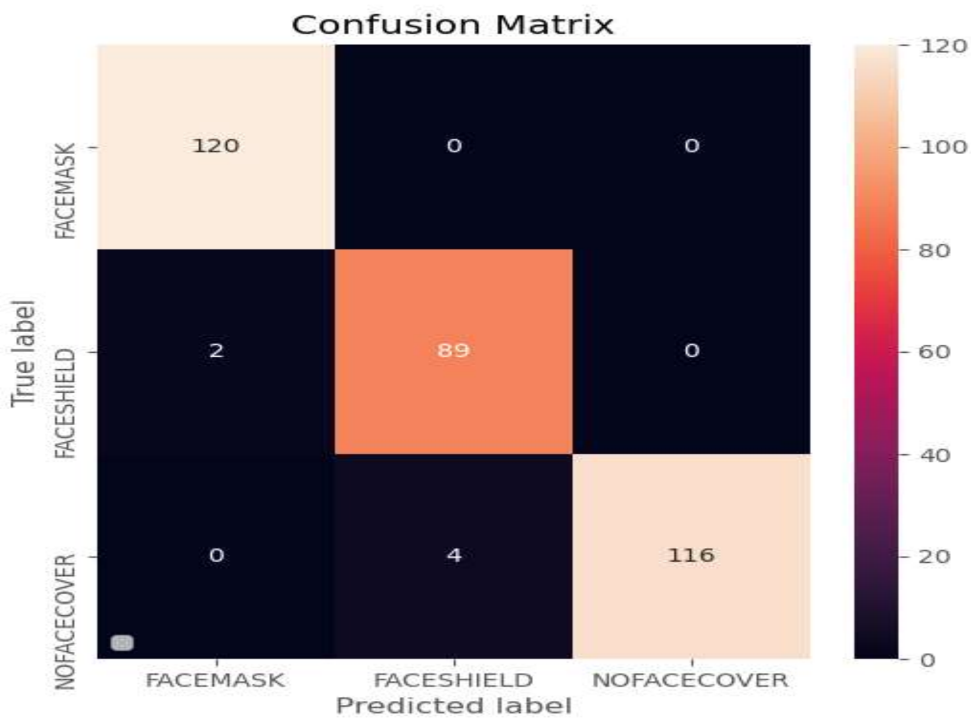

Figure 10. Model Confusion Matrix

Figure 10 is the confusion matrix for the model validation set. The statistics show the number of images that were correctly classified and those that were not correctly classified after 20 iterations. 325 out of a total of 331 images were correctly classified, and only 6 images were not classified correctly. 120 of the correctly classified were of those with face masks, 89 were those wearing face shields and the remaining 116 were of those without face shields or masks. The confusion matrix also shows that no image of a mask or shield was classified as not having face cover. This results in an accuracy, average precision and recall of approximately 98%, as shown in figure 11.

[INFO] evaluating network...

	precision	recall	f1-score	support
FACEMASK	0.98	1.00	0.99	120
FACESHIELD	0.96	0.98	0.97	91
NOFACECOVER	1.00	0.97	0.98	120
accuracy			0.98	331
macro avg	0.98	0.98	0.98	331
weighted avg	0.98	0.98	0.98	331

Figure 11. Model Validation Accuracy and Classification Report

Model application

Given the accuracy of the model, it is hopeful that the model will generalize well when images outside of the training and validation set are fed to it. In order to do that, the model was saved on the disk. A different image was fed to see whether it would detect and classify the image on the face detector.

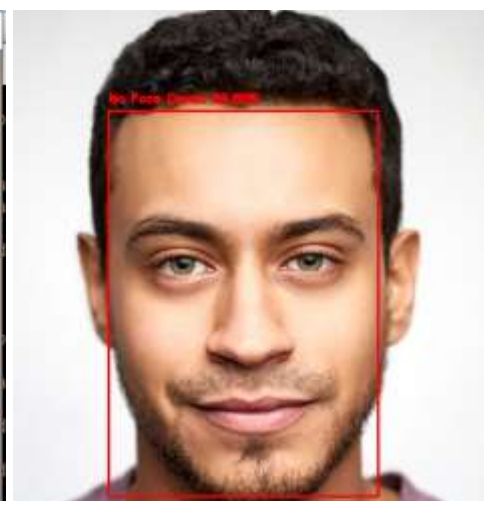

Figure 12. Face Mask Detected *Figure 13. Face Shield Detected* *Figure 14. Face Shield or Mask not Detected*

Figures 12, 13 and 14 display the results of the face detector application in detecting whether a person is putting on a mask, shield or not. Figures 12 and 13 detected a mask and a shield respectively, with very high accuracy, while Figure 14 displayed that the person was not wearing any face cover with approximately 100% accuracy. In this case, the system can trigger an alarm to prompt the administrator to take action against the individual.

CONCLUSION

This research developed a face detector with the help of transfer learning using MobileNetV2 architecture to classify whether a person is wearing a face cover or not. Image augmentation, a preprocessing technique, was used to enhance the performance of the model as they increased the diversity of the training data. The developed model achieved an accuracy, precision, and recall rate of 98%. The work presents a useful tool in fighting the spread of the COVID-19 virus by detecting a person not wearing a shield or a mask. The major contribution of this research is that a pretrained model detector that automatically finds and detects faces covered with shields and masks was developed.

LIMITATIONS OF THE STUDY

Face shields come in a variety of shapes and sizes to suit different kinds of applications. No specific type of shield was considered when designing the model for this study, as a different variety of face shields were scraped. This may have an impact on the model's ability to generalize with previously unseen data, either positively or negatively. Furthermore, the majority of the scraped face shields were of frontal view, which caused the model to perform poorly when images of side view were shown to the model.

RECOMMENDATION

It is recommended that the work be further improved by employing large volumes of data in order to get 100% accuracy and can also be extended to classify other types of PPE. Other lightweight models can be developed with an integrated facial recognition system and deployed at various workplaces to support person identification, so people not wearing a face shield or mask can be fined while others are rewarded.

REFERENCES

Agarwal, S., Punn, N.S., Sonbhadra, S.K., Nagabhushan, P., Pandian, K. & Saxena, P. (2020). Unleashing the power of disruptive and emerging technologies amid covid 2019. A detailed review. *arXiv preprint arXiv:2005.11507*

Ahmed, F.G. (2018). Practical computer vision applications using deep learning with CNNs. *Apress*, Menoufia, Egypt. ISBN-13 (electronic): 978-1-4842-4167-7.

Al-Mamun, G.M.S.U. & Kabir, F. (2021). Design and management of cloud assisted smart ICU for Covid-19 patients real-time health parameters measurement based on IoT's through wireless sensor network. *International Research Journal of Science, Technology, Education, and Management, 1*(2), 78-96. https://doi.org/10.5281/zenodo.5726340

Bhandary, P. (2020). *GitHub*. Retrieved from https://github.com/prajnasb/observations

Chen, Y., Hu, M., Hua, C., Zhai, G., Zhang, J., Li, Q., & Yang, S. X. (2020). Face Mask Assistant: Detection of Face Mask Service Stage Based on Mobile Phone. *arXiv preprint arXiv:2010.06421*

Chowdary, G.J., Punn, N.S., Sonbhadra, S.K. & Agarwal, S. (2020). Face Mask Detection using Transfer Learning of InceptionV3. *arXiv preprint arXiv:2009.08369v.2*

Ejaz, Md.S., Islam, Md.R., Sifatullah, M. & Sarker, A. (2019). Implementation of Principal Component Analysis on Masked and Non-masked Face Recognition. *2019. 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT),* 1–5. https://doi.org/10.1109/ICASERT.2019.8934543

Feng, S., Shen, C., Xia, N., Song, W., Fan, M. & Cowling, B.J. (2020). Rational use of face masks in the covid-19 pandemic. *The Lancet Respiratory Medicine, 8*(5), 434-436.

Geroso, P.J.M. & Aloba, R. (2021). Teachers' and parents' support on learners' academic stress amidst pandemic. *International Research Journal of Science, Technology, Education, and Management, 1(*2), 136- 149. https://doi.org/10.5281/zenodo.5726548

Howard, J., Huang, A., Li, Z., Tufekci, Z., Zdimal, V., van der Westhuizen, H.M. & Rimoin, A.W. (2021). An evidence review of face masks against COVID-19. *Proceedings of the National Academy of Sciences*, *118*(4).

iStock. (n.d.). *Face Mask*. https://www.istock.com/search/facemask

Loey, M., Manogaran, G., Taha, M.H.N. & Khalifa, N.E.M. (2020). A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic. *Measurement, 167*, 108288. https://doi.org/ 10.1016/j.measurement.2020.108288

Loey, M., Manogaran, G., Taha, M.H.N. & Khalifa, N.E.M. (2020). Fighting against COVID-19: A novel deep learning model based on YOLO-v2 with ResNet-50 for medical face mask detection. *Sustainable Cities and Society, 102600.*

Marketing (2019). *Transfer Learning Made Easy: Coding a powerful technique*. Exxact. https://blog.exxactcorp/transfer-learning-made-easy/

Matrajt, L. & Leung, T. (2020). Evaluating the efficacy of social distancing strategies to postpone or flatten the curve of coronavirus disease. *Emerging Infectious diseases*, 26(8), 1740.

Mundell, E.J. (2020). *Are face shields better than face masks for coronavirus?* MedicineNet. https://www.medicinenet.com/script/main/art.asp?articlekey=230978

Pan American Health Organization (2020). *COVID-19 has infected some 570,000 health workers and killed 2,500 in the Americans.* PAHO news. www.paho.org/en/news/2-9-2020-covid-19-has-infected-some-570000-health-workers-and-killed-2500-americas-paho

Perencevich, E.N., Diekema, D.J. & Edmond, M.B. (2020). Moving personal protective equipment into the community: face shields and containment of COVID-19. *Jama*, *15*(1), 40-45.

Qin, B. & Li, D. (2020). Identifying facemask-wearing condition using image super- resolution with classification network to prevent covid-19. *arXiv preprint arXiv:2005.01385*

Ristea, N.C. & Ionescu, R.T. (2020). Are you wearing a mask? Improving mask detection from speech using augmentation by cycle-consistent GANs. *arXiv preprint arXiv:2006.10147v2*

Ritchie, N. (2018). *Evaluating a classification model.* Ritchie Ng. https://www.ritchieng.com/machine-learning/

Rosebrock, A. (2017). *Deep Learning for Computer Vision with Python.* Pyimagesearch. https://www.pyimagesearch.com/deep-learning-computer-visionpython-book/

Rosebrock, A. (2020). *COVID-19 Face Mask Detector with OpenCV, Keras/TensorFlow, and Deep Learning*. PyimageSearch. https://www.pyimagesearch.com/2020/05/04/COVID-19-Face-Mask-Detector-with-OpenCV-Keras_TensorFlow-and-Deep-Learning/

Sandler, M., Howard, A., Zhu, M., Zhmoginov, A. & Chen, L.C. (2018). MobileNetV2: Inverted Residuals and Linear Bottlenecks. *arXiv preprint. arXiv:1801.04381, 2018*

Sangha (2020). *Transfer Learning: A shortcut for training deep learning models*. Artificial Intelligence. https://medium.com

Shutterstock. (n.d.). *Faceshield Images*. https://www.shutterstock.com/search/face+shield

Sonbhadra, S.K., Agarwal, S., & Nagabhushan, P. (2020). Target specific mining of covid-19 scholarly articles using one-class approach. *arXiv preprint arXiv:2004.11706*

Ting, D.S.W., Carin, L., Dzau, V. & Wong, T.Y. (2020). Digital technology and covid-19. *Nature medicine 26*(4), 459-461.

Ud Din, N., Javed, K., Bae, S. & Yi, J. (2020). A Novel GAN-Based Network for Unmasking of Masked Face. *IEEE Access*, *8*, 44276–44287. https://doi.org/10.1109/ACCESS.2020.2977386

Wang, C., Horby, P.W., Hayden, F. G. & Gao, G.F. (2020). A novel coronavirus epidemic of global concern for health. *The Lancet*, 395(10223), 470-473.

Witten, I.H. & Frank, E. (2005). *Data Mining: Practical Machine Learning Tools and Techniques. (2nd ed).* Morgan Kaufmann. https://www.researchgate.net/publication/30876208_Data_mining_Practical_machine_Learning_Tools_and_Techniques

World Health Organization. (2020). *World Health Organization Newsletter*. https://www.who.int