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Advancements in Machine Learning-Based Face Mask Detection: A Review of Methods and Challenges

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ABSTRACT- Wearing face masks is crucial in various environments, particularly where there is high potential of viral transmission. Proper wearing of face masks always is important in hospitals and healthcare facilities where the risk of transmission of different contagious diseases is very high. The COVID-19 pandemic has been recognized as a global health crisis, exerting deep impacts on various sectors such as industry, economy, public transportation, education, and residential domains. This rapidly spreading virus has created considerable public health risks, resulting in serious health consequences and fatalities. Wearing face masks in public locations and crowded regions has been identified as one of the most effective preventive methods for reducing viral transmission. Using powerful face mask detection systems in such contexts can thus significantly improve infection control efforts while protecting the health and well-being of healthcare personnel, patients, and visitors. In this paper, we present a comprehensive review of recent advancements in machine learning techniques applied to face mask identification. The existing approaches in this sector can be broadly categorized into three main groups: mask/no mask detection approaches, proper/improper mask detection approaches, and human identification through masked faces approaches. We discuss the advantages and limitations associated with each approach. Further, we explore into the technical challenges encountered in this field. Through this study, we aim to provide researchers and practitioners with a comprehensive understanding of the state-of-the-art machine learning techniques for face mask detection.

Keywords: Face mask detection; proper mask detection; masked face identification; facial recognition; Covid-19; contagious disease transmission.

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1. INTRODUCTION

COVID-19 is a global pandemic that has caused a worldwide health crisis and has had a significant impact on a variety of industries and life activities. COVID-19, a pandemic illness, spread quickly over the world, causing a worldwide health and humanitarian crisis. It also had a significant influence on people's daily life. Therefore, the World Health Organization (WHO) declared that wearing face masks in public places is one of the most efficient protective strategies [1]. Facemasks should be worn as part of an overall precautionary plan to avoid spread of the virus. Moreover, many public service providers require customers to utilize their facilities while donning face masks that fulfill specified requirements. These findings motivated the research in automated facemask identification that might improve in public behavior monitoring and help to limit the pandemic spread [2]. These systems can be implemented in health care centers, schools, industrial and commercial sectors, and public transportation.
In addition, it is of high importance to consistently wear face masks within hospitals and healthcare establishments, where the potential for spreading of numerous infectious diseases is greatly high. The implementation of resilient face mask detection systems in these settings can greatly enhance infection control endeavors, effectively safeguarding the health and welfare of medical personnel, patients, as well as individuals visiting such facilities. As a result, the development of robust face mask detection systems is critical in preventing the spread of viruses and dangerous diseases. In this work, we explain, analyze, and compare recent ML-based face mask detection methods and highlight the technical issues observed in this domain.

2. BACKGROUND

Machine learning (ML) is a subfield of Artificial Intelligence (AI) that simulates human learning through examples to identify patterns in data and generate predictions. Deep learning (DL) is a subset of ML that can learn without the need for human intervention, using both labeled and unlabeled data. Deep learning techniques, on the other hand, may be excessive for simpler tasks because they require access to a large amount of data to be effective [3] [4] [5] [6]. Because of their high accuracy and speed, DL algorithms have had a significant impact on object detection and classification are essential AI components. [7] [8] [9] [10].

Convolutional neural networks (CNN) architecture is one of

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the well-known DL techniques that has been most applied to image classification tasks. A typical CNN architecture, as illustrated in *figure 1*, has many convolution layers where filtering is performed to input images to extract image features [11] [12] [13]. Following the convolution layer, a non-linear activation function is applied. Hyperbolic tangent, Sigmoid and Rectified Linear Unit (ReLU) are the most used activation functions in CNN networks. After that, a pooling layer is usually applied in order to reduce the size of the image. In CNN architectures, the sequence of convolutional layers, activation functions, and pooling layers is finally concluded with a fully connected neural network layer where the classification task is performed [14] [15] [16] [17].

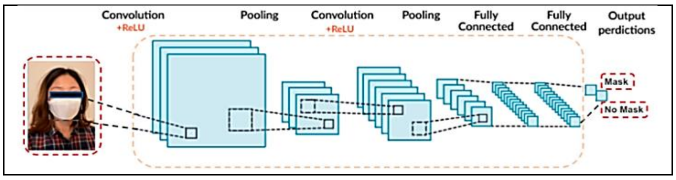

Figure 1: CNN Architecture for Mask Detection [11].

3. CURRENT APPROACHES

The machine learning face masks detection methods can be categorized into three main types: mask/no mask detection, proper/improper mask detection, and human authentication through masked faces. The current methods are summarized and discussed in this section.

3.1. Mask/No Mask Detection

Jiang et al. [18] presents Retina Facemask as a transfer learning-based face mask detection approach. The approach combines a feature pyramid network that incorporates higher-level semantic details alongside a unique context attention unit to focus on recognizing face masks. The architecture of Retina Facemask is illustrated in *figure 2* and the context attention module is presented in *figure 3*.

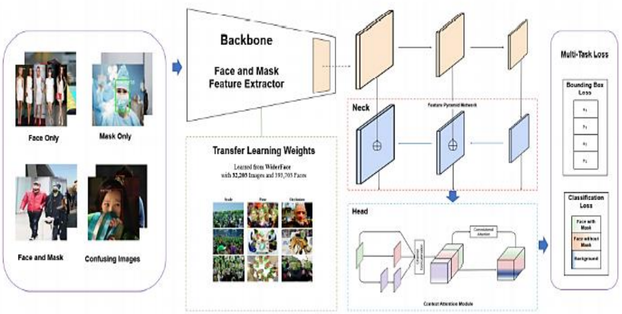

Figure 2: Architecture of Retina Facemask [18].

Experiment findings indicate that Retina Facemask showed reasonable performance on a public face mask dataset. The dataset contains 7959 images which was partitioned to a training, validation, and testing subsets of 4906, 1226, and 1839 instances, respectively. The face and mask recognition precision are 2.3% and 1.5% greater than baseline, respectively, and recall is 11.0% and 5.9% greater than baseline. It looks at the potential of using a light-weighted neural network MobileNet to construct a Retina Facemask for embedded or mobile devices.

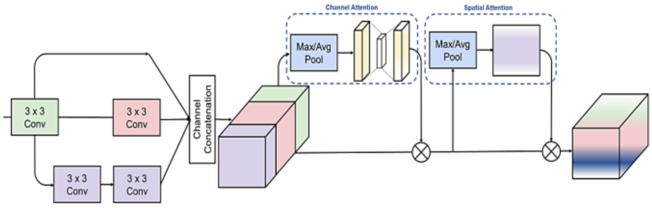

Figure 3: Context Attention Detection Module [18].

Loey et al. [19] presents a hybrid approach that combines deep transfer learning and classical ML as shown in *figure 4*. The feature extraction stage is performed through Resnet50 as a DL approach as shown in *figure 5*. The classification stage is performed through three ML techniques which are Decision-Tree (DT), Support-Vector-Machines (SVM), and ensemble classifier. Three masked-face image sets were utilized for evaluation which are RMFRD [20], SMFD [21], LFW [22]. The SVM classifier demonstrated the best performance with accuracies of 99.64% in RMFRD, 99.49% in SMFD, and a perfect 100% in the LFW dataset.

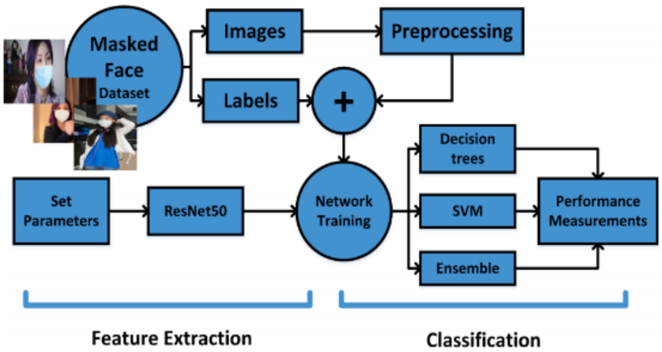

Figure 4: The hybrid deep transfer learning model [19].

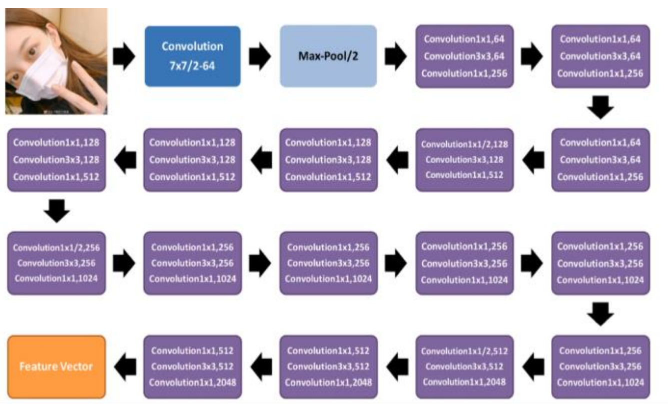

Figure 5: ResNet-50 as the feature extractor [19].

Chavda et al. [23] present a deep transfer learning approach through 3 CNN models; MobileNetV2, DenseNet121, and

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NASNet to classify face images into 3 categories; proper-mask, improper-mask and no-mask covering. Masked face data were collected from RMFRD [20] in addition to the Face Mask Detection dataset on Kaggle [24]. The classification accuracy is 99.12% for MobileNetV2, 99.40% for DenseNet121, and 99.13% for NASNet.

Nagrath et al. [25] presents a single shot multibox detector and MobileNetV2 (SSDMNV2) face masks detection approach using based on DL, TensorFlow, Keras, and OpenCV. The approach utilizes the single shot multibox face detector and the MobilenetV2 model as a CNN classifier. The system is lightweight and suitable for deployment on embedded devices such as the NVIDIA Jetson Nano and Raspberry Pi. This enables real-time mask detection capabilities on these platforms. The SSDMNV2 model is demonstrated in *figure 6* and the MobileNetV2 architecture is illustrated in *figure 7*. The dataset used in this method includes 5521 masked-faces and 5521 unmasked-faces. This data was collected from various open-source datasets including RMFRD [20]. MobileNetV2 model achieved 92.64% classification accuracy and 93% F1 score.

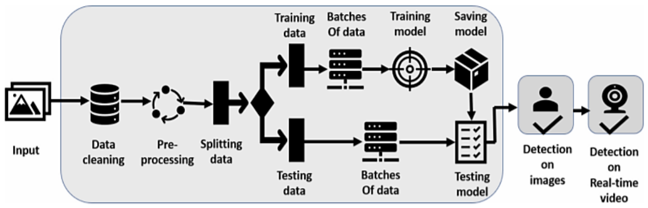

Figure 6: Flow Diagram of the SSDMNV2 model [25].

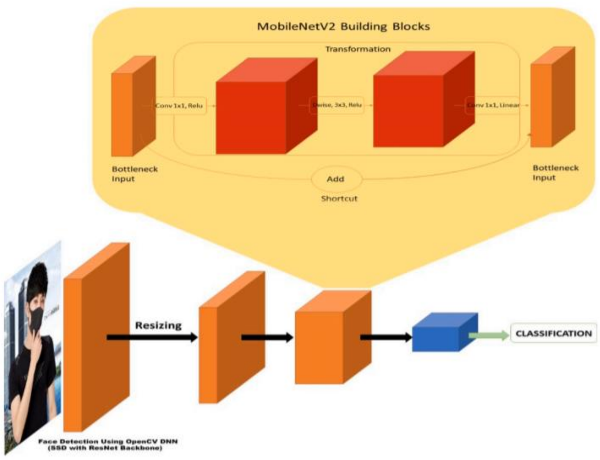

Figure 7: Architecture of MobileNetV2 [25].

3.2. Proper/Improper Mask Detection

Effective mask recognition systems are essential to identify that people are wearing masks accurately in controlled areas. Therefore, a large dataset is necessary to train and test ML/DL models to identify people wearing masks correctly or incorrectly. Aydemir et al. [26] presents a technique that uses deep learning to address the issue of improper mask usage. A dataset of 2075 people using face masks were collected. Each image is labeled as proper-mask, improper-mask, or no-masked. The dataset can be accessed at https://websiteyonetimi.ahievran.edu.tr/_Download/MaskDataset.rar. This approach consists of three major pre-trained steps. As feature generators, ResNet101 and DenseNet201 were used as shown in *figure 8*. Second, an improved RelieF selector was used to choose the most discriminative characteristics. Finally, a SVM classifier was evaluated on three different classification tasks. The first task is about mask versus no mask versus improper mask classification. The second task is mask versus no mask and improper mask classification while the third task is mask versus no mask classification. The proposed model demonstrated classification accuracies of 95.95%, 97.49%, and 100% on the three tasks, respectively.

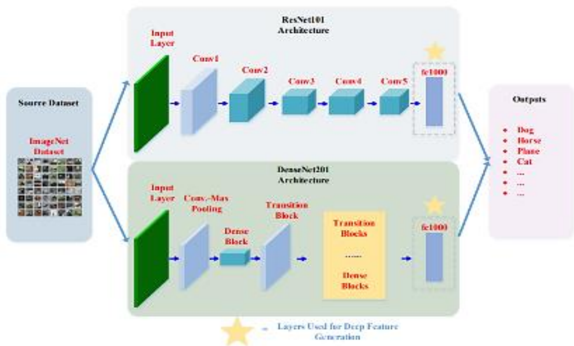

Figure 8: ResNet101 and DenseNet201 deep network architectures [26].

Kasap et al. [27] introduces an approach that uses a large dataset to analyze different transfer learning networks that enables the identification of individuals who are wearing masks, as well as the assessment of whether the masks are being worn correctly even when their face is captured in low-resolution and from different angles. The face mask dataset (Face Mask Detection) used in this study's tests is available publicly at https://makeml.app/datasets/mask and it consists of 853 images in total, each of which has one or more people who fall into one of the three groups "Masked," "Unmasked," or "Mask Incorrectly Worn" as shown in *figure 9*.

Figure 9: Images from the dataset showing faces with *(a)* appropriately worn masks, *(b)* no masks, and *(c)* wrongly worn masks [27].

The transfer learning models examined are ResNet50, InceptionV3, Xception, VGG16, VGG19, MobileNet, and EfficientNetB7. The division of these datasets was consistent across all models, with 80% allocated for training, 10% for validation, and 10% for testing. The authors reported that ResNet50 exhibited superior performance compared to the other models, achieving an accuracy rate of 99% while InceptionV3 was the least. In terms of training time, MobileNet it is the fastest model. The advantages of this method are it uses low layers architecture for detection, and it

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succeeded with rates between 86% and 99%. Also, all training models achieved low loss rates. However, the method is limited in scenarios involving the use of facial shields, transparent masks, or masks with texturing approximating human faces.

Dellosa et al. [28] proposed a system using the YOLOv3 as a deep learning technique to improve face mask identification as shown in *figure 10*. The image dataset used in this research is sourced from MaskedFace-Net [29]. The dataset comprises 70,000 high-quality PNG photos with a resolution of 1024x1024. It includes diverse backgrounds, age groups, and ethnicities, as well as various accessories such as hats, sunglasses, and eyeglasses. The model performed well with a remarkable total accuracy score of 98.85%, indicating that YOLOv3 is effective in distinguishing between correct and incorrect face mask usage in controlled environments.

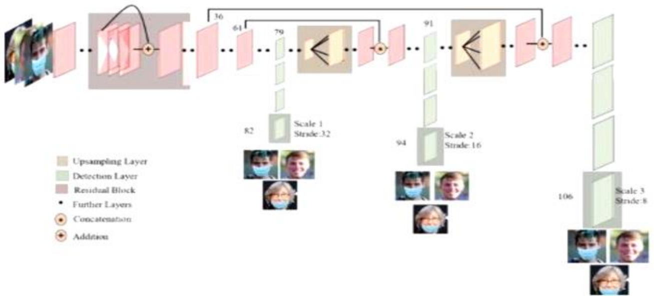

Figure 10: Yolov3 Architecture [28].

3.3. Masked Faces Human Authentication

Hariri [30] proposes an occlusion removal and DL-based features extraction masked face recognition approach. The first stage of the approach is to identify masked facial regions. Then, it utilizes three pre-trained deep CNN models: VGG-16, AlexNet, and ResNet-50 for extracting deep features from the resulting areas. Finally, the classification process is carried out using Multilayer Perceptron (MLP) as shown in *figure 11*. This system is evaluated on two open-source datasets: RMFRD [20] and SMFRD [31]. The recognition rate is 91.3% on RMFRD dataset and is 88.9% on SMFRD dataset.

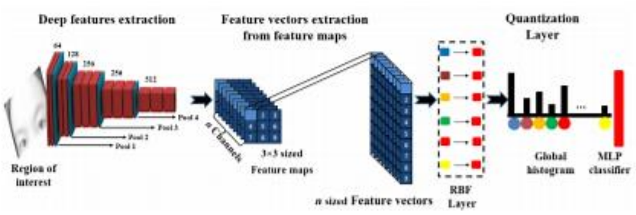

Figure 11: Overview of Hariri proposed method [30].

Aswal et al. [32] presents a masked face person identity retrieval. First, masked faces are located through the YOLO-face [33] and RetinaFace [34]. Then, VGGFace2 [4] determines the facial feature vectors in combination with a nearest neighbor identity recognition technique. The flowchart of the proposed identification system is shown in *figure 12*. The dataset employed was created from 17 real-world video examples for 7 individuals with various orientations, illuminations, and occlusions. Experimental outcomes indicate that RetinaFace and VGGFace2 attain an overall performance of 92.7%, with a facial detection accuracy of 98.1% and a facial authentication accuracy of 94.5%. The backbone architecture of VGGFace is ResNet-50 CNN which was pretrained using the softmax loss function on datasets having 3.31 million images classified into 9131 persons, with differences in ethnicity, age, and pose. The VGGFace2 process produces a 2048 vector dimensional descriptor face embedding.

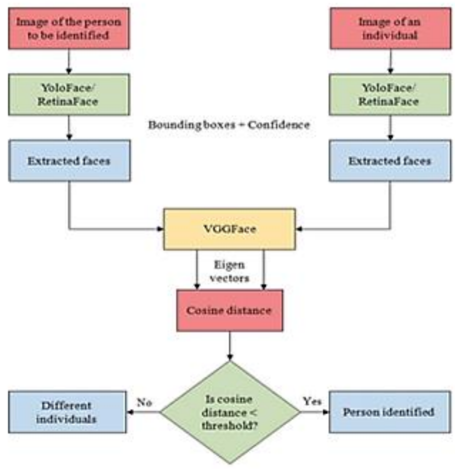

Figure 12: Flowchart of the identification system proposed by [32].

Ding et al. [35] collects two labeled datasets where the first dataset encloses 400 images of 200 individuals, while the second dataset encloses 4,916 images of 669 individuals. They propose a data augmentation approach for creating virtual images from existing ones in order to improve CNN model training and avoid overfitting. Further, they introduced a new latent part detection (LPD) method to identify the covered portion of the face. The architecture of the proposed method is shown in *figure 13*. Experimental results demonstrated that LPD approach works effectively on both real and virtual masked images achieving a high level of accuracy of 94.34%. The code is available at https://gitee.com/ffeiding/Masked-Face-Recognitionwith-Latent-Part-Detection.

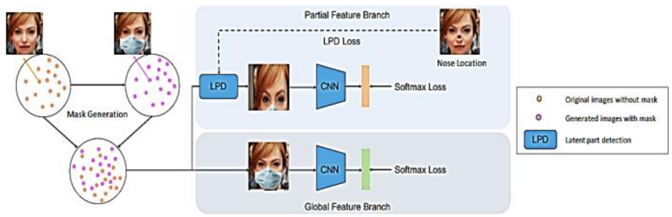

Figure 13: Architecture of the method proposed by [35].

Shatnawi et al. [36] proposed a deep transfer learning method to identify individulas through their masked faces. A dataset of 400 masked-face images for ten different individuals was created. Then, six pre-trained CNN networks were evaluated on this dataset. The networks are SqueezeNet, GoogleNet, AlexNet, ResNet-50, VGG-16, and MobileNet-V2. When

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tested on unseen data, all the six networks achieved 100% recognition accuracy with very high confidence level. All the above approaches are summarized and compared in *table 1*.

4. TECHNICAL CHALLENGES

Facial recognition is considered one of the complex pattern recognition tasks as facial images appearance could significantly vary. Although face recognition approaches have achieved significant performance in well-controlled environments, these approaches do not do well in real-life scenarios where the face images of a certain individual look different due to several reasons including lighting variations, head pose variations, facial expressions, ageing , plastic surgery, low resolution and occlusion [37], [38], [39], [40], [41], [42], [43].

Privacy concerns and ethical considerations is one of the great challenges. Face mask recognition involves capturing and analyzing individuals' facial data. Ensuring the ethical use of this technology and protecting privacy rights are critical open issues.

Table 1: Summary of the ML-based faced mask detection approaches.

Article	Approach and Model	Dataset	Performance
Jiang et al. [18]	Mask/No Mask Detection with Retina Facemask, Feature Pyramid Network, Context Attention Unit, MobileNet	Public face mask dataset (7959 images)	Precision: 2.3% (face), 1.5% (mask) greater than baseline Recall: 11.0% (face), 5.9% (mask) greater than baseline
Loey et al. [19]	Mask/No Mask Detection with Hybrid Approach (DL & classical ML) Decision-Tree, SVM, Ensemble Classifier	RMFRD, SMFD, LFW datasets	Accuracy: 99.64% (RMFRD), 99.49% (SMFD), 100% (LFW)
Chavda et al. [23]	Mask/No Mask Detection with DL. MobileNetV2, DenseNet121, NASNet CNN models	RMFRD, Kaggle Face Mask Detection datasets	MobileNetV2: 99.12% DenseNet121: 99.40% NASNet: 99.13%
Nagrath et al. [25]	Mask/No Mask Detection with Single Shot Multibox Detector, and MobileNetV2	Various open-source datasets including RMFRD (5521 masked-faces, 5521 unmasked-faces)	Accuracy: 92.64%, F1 score: 93%
Aydemir et al. [26]	Proper/Improper Mask Detection with DL. ResNet101, DenseNet201 Improved RelieF selector SVM classifier	Custom dataset of 2075 people	Proper/Improper/No-Mask Accuracy: 95.95%, 97.49%, 100%
Kasap et al. [27]	Proper/Improper Mask Detection with DL. ResNet50, InceptionV3, Xception, VGG16, VGG19, MobileNet, and EfficientNetB7.	Face Mask Detection dataset (853 images)	ResNet50 accuracy: 99%
Dellosa et al. [28]	Proper/Improper Mask Detection with YOLOv3	MaskedFace-Net dataset (70,000 images)	Total accuracy: 98.85%
Hariri [30]	Masked Faces Human Authentication with DL. VGG-16, AlexNet, ResNet-50 for extracting deep features MLP for classification	RMFRD, SMFRD datasets	Recognition rate: 91.3% (RMFRD), 88.9% (SMFRD)
Aswal et al. [32]	Masked Faces Human Authentication with YOLO-face, RetinaFace, and VGGFace2.	Custom dataset (from 17 real-world video examples for 7 individuals with various orientations, illuminations, and occlusions.)	Facial detection accuracy: 98.1% Facial authentication accuracy: 94.5%
Ding et al. [35]	Masked Faces Human Authentication with Latent Part Detection (LPD)	Two labeled datasets (the first dataset encloses 400 images of 200 individuals, while the second dataset encloses 4,916 images of 669 individuals)	Accuracy: 94.34%
Shatnawi et al. [36]	Masked Faces Human Authentication with DL. SqueezeNet, GoogleNet, AlexNet, ResNet-50, VGG-16, MobileNet-V2	Custom dataset (400 masked-face images for ten different individuals)	Accuracy: 100%

In some cases, faces can be partially blocked by other faces or objects especially when many people are involved. However, it makes it difficult to recognize a face, even if a face was recognized it might or might not be accurate due to the hidden parts of the face. Facial occlusion can happen in another form such as wearing sunglasses, scarfs, irregular mask shape, etc. All these factors are so critical and can affect the performance of a face recognition system. Hairstyles can also be adjusted to modify the look of the face picture or to conceal facial traits. Moreover, motion blur, dynamic focus and frame transition are some of the challenges faced in video feed analysis [44].

Most people wear masks in public these days, posing new challenges to the face detection and identification system. Most of the face mask systems may have some issues with the resolution of the camera which might be a limitation due to some influences like light intensity and distance.

Selecting the best technique for masked-face identification system is a big challenge. There are numerous ML and DL techniques that vary in accuracy, computational cost, and ability to avoid over-fitting. Therefore, all of these challenges must be considered in selecting a good technique [45]. In addition, there are very few available masked face datasets. Most of these datasets either consist of synthetically generated data that does not accurately represent real-world scenarios or they suffer from noise and erroneous labeling [25] [46] [47]. As a result, the availability of large, comprehensive, and accurate benchmark datasets is needed for training and evaluation of masked-face identification techniques.

Addressing these challenges requires continued research and innovation in machine learning and computer vision techniques, robust data collection methodologies. Collaboration between researchers, industry experts, and policymakers is crucial to develop robust, accurate, and ethically sound face mask recognition systems.

5. CONCLUSIONS

This paper provides an overview of face mask detection systems and their significance in protecting public safety. The study outlines the basic ideas underlying these systems, which include detecting the presence of masks on people's faces and recognizing persons even when they are wearing masks. Recent approaches to face mask detection have been divided into three categories: mask detection, proper/improper mask wearing detection, and human identification using masked faces. The development of such systems is critical in providing a safe environment for individuals and communities, especially during pandemics and in medical facilities. Additionally, the paper has shed light on the main technical challenges that should be addressed to further advance this field and inspire the development of more robust and accurate models. Although face mask detection using machine learning has gained considerable attention in recent times, the field is continuously growing with rapid advancements. Researchers should constantly explore new methodologies, architectures, and datasets to improve the accuracy, efficiency, and robustness of face mask detection systems. Face mask detection has applications beyond the current context, such as in healthcare settings, security systems, and human-computer interaction. Despite the progress made, there are still several unexplored challenges in face mask detection. Overcoming these challenges requires continuous research, innovation in machine learning and computer vision techniques, and the establishment of robust data collection methodologies. Moreover, fostering collaboration among researchers, industry experts, and policymakers is essential to enhance the development of reliable, accurate, and ethically sound face mask recognition systems, and in turn, improve safety measures and public health protection.

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