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A Systematic Review On CNN For Face Mask Detection: Current Trends And Future Directions

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Abstract: The COVID-19 pandemic has necessitated the development of face mask detection systems to enforce safety measures and monitor compliance. This abstract provides an overview of various datasets and approaches used for face mask detection using Convolutional Neural Networks (CNN). The datasets described include NO-MASK, UMD Faces, Annotated facial landmarks in the wild, UMD Masks, FDNA, and more. Researchers have created large-scale datasets such as NO-MASK, UMD Masks, and UMD Faces, which provide annotated images for training deep networks. These datasets have played a vital role in advancing face mask detection algorithms. Additionally, datasets like COVID-19 screening on chest X-ray images have been used for anomaly detection and screening purposes. Numerous deep learning approaches have been proposed for face mask detection. Techniques such as neural networks with augmentation, vision-based frameworks, deep learning-based anomaly detection, and hybrid fusion frameworks have been utilized. These approaches aim to accurately identify and classify faces with or without masks.

I. Introduction:

Face mask detection has become a critical task in recent years, particularly during the COVID-19 pandemic, as it plays a vital role in safeguarding public health and safety. Accurate and efficient face mask detection systems are essential for various applications, including public spaces, healthcare facilities, and surveillance systems. CNN have emerged as a powerful tool for detecting and classifying objects in images, making them well-suited for face mask detection.

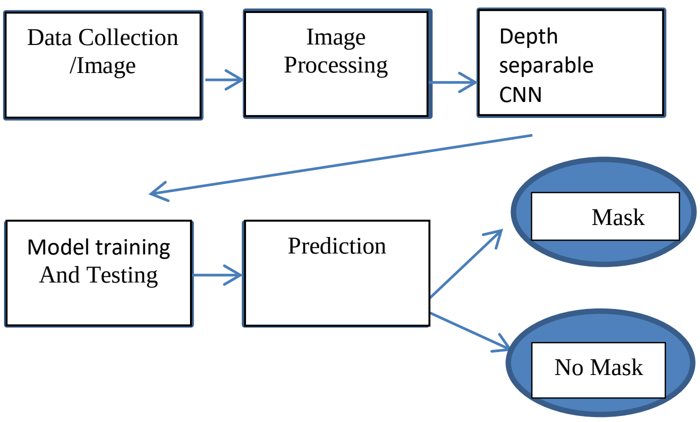

Figure - 1 Flow Diagram of Result Prediction using CNN

CNNs have demonstrated impressive performance in numerous computer vision tasks, including object recognition, detection, and segmentation. Their ability to learn and extract meaningful features from visual data makes them highly effective for face mask detection. By leveraging the hierarchical structure of CNNs as shown in Figure-1, these models can automatically learn discriminative features from face images, enabling them to accurately differentiate between individuals wearing and not wearing face masks.To train and evaluate face mask detection systems, researchers have developed and utilized various benchmark datasets. The WIDER FACE dataset [1] is one such dataset that provides a large-scale collection of face images captured in diverse and unconstrained settings. It serves as a benchmark for face-related tasks, including face detection. The FDDB dataset [2] and Labeled Faces in the Wild (LFW) dataset [3] are other well-known datasets used for face-related tasks, allowing researchers to develop robust and generalized face mask detection models.

In recent years, specialized datasets specifically designed for face mask detection have been created. The AFDB dataset [4] and RMFD dataset [5] are examples of large-scale datasets that contain a significant number of images with individuals wearing different types of face masks in various scenarios. These datasets enable researchers to develop and evaluate face mask detection models in a more focused and targeted manner. Additionally, the MED-FD dataset [6] focuses on detecting mask-wearing status in medical environments, which is crucial for healthcare applications. Researchers have proposed various CNN-based approaches for face mask detection. Hrishikesh et al. [7] introduced a deep learning approach that utilizes CNNs to classify face images into "with mask" and "without mask" categories. Their model achieved high accuracy in detecting face masks. Alam et al. [8] developed a dataset and a corresponding CNN-based framework specifically designed for detecting mask-wearing status in medical environments. These studies highlight the potential of CNNs in effectively addressing the challenges associated with face mask detection.
Face mask detection using CNNs holds significant promise in contributing to public health measures and safety protocols. By leveraging large-scale benchmark datasets and specialized datasets for face mask detection, researchers continue to develop and improve CNN-based models to enhance the accuracy, efficiency, and robustness of face mask detection systems. These advancements have the potential to positively impact various domains, including public health, transportation, and security.In Whole, CNN-based approaches have demonstrated notable performance in face mask detection, offering a powerful solution to address the challenges posed by the COVID-19 pandemic. Leveraging benchmark datasets and specialized datasets, researchers are making significant strides in developing accurate and efficient face mask detection models, as described in Figure-2 when input and output are explained with the K*w* and K*h* combination results in detection and identification. As the field continues to advance, CNN-based techniques are expected to play a crucial role in ensuring public health and safety in various real-world applications.

II. Methodologies for Facemask Detection

Facemask detection involves the application of various methodologies and techniques, ranging from traditional computer vision approaches to state of the art deep learning based methods. This section aims to discuss these methodologies, their advantages and limitations, and any notable advancements or innovative approaches within each category.

Traditional Computer Vision Approaches: Traditional computer vision approaches for facemask detection involve a series of steps, including face detection, feature extraction, and classification. Let's dive into each step in more detail:

1. Face Detection:

Face detection is the initial step in the process, aiming to locate and identify faces in an image or video frame. Haar cascades and the Viola-Jones algorithm are commonly used techniques for face detection. These methods utilize a set of pre-trained classifiers that are trained to identify specific facial features, such as the presence of eyes, nose, and mouth. By scanning the image or frame with these classifiers, potential face regions are identified.

2. Feature Extraction:

Once the faces are detected, the next step is to extract meaningful features from the face regions. Various feature extraction techniques have been used in traditional computer vision approaches for facemask detection. Some common methods include:

a. Histogram of Oriented Gradients (HOG): HOG computes the distribution of gradient orientations within local image patches. It captures shape and edge information and has been widely used for object detection tasks, including face-related applications.

b. Local Binary Patterns (LBP): LBP encodes the relationship between pixels in a local neighborhood. It describes texture information and has been employed for various pattern recognition tasks, including facial analysis.

c. Scale-Invariant Feature Transform (SIFT): SIFT detects and describes distinctive local features within an image. It is robust to changes in scale, rotation, and illumination and has been utilized for face recognition and feature matching tasks.

These feature extraction techniques aim to capture relevant information from the face regions, which can later be used for classification.

3. Classification:

After feature extraction, a classification algorithm is employed to determine whether a person is wearing a mask or not. Commonly used classifiers in traditional computer vision approaches include Support Vector Machines (SVM), Random Forests, and other classical machine learning algorithms. These classifiers are trained on labeled datasets, where the extracted features are associated with corresponding labels (mask or no-mask). Once trained, the classifier can predict the presence or absence of a facemask based on the extracted features.

Advantages of traditional computer vision approaches for facemask detection include their interpretability and relatively low computational requirements. These methods can provide reasonable performance in scenarios with limited variations in lighting conditions and mask types. They have been extensively used in research and practical applications. Additionally, these approaches are based on well-established techniques and do not require large amounts of training data.

However, traditional computer vision approaches have limitations. They often struggle with handling occlusions, where the face is partially covered by objects or other people. They can also face challenges when dealing with variations in mask types, such as different colors, styles, or patterns. Complex backgrounds and variations in lighting conditions can further impact the performance of these methods. Additionally, feature engineering in traditional approaches can be a time-consuming and labor-intensive process, requiring domain knowledge and expertise to design effective features.

As computer vision advances, modern deep learning approaches, such as convolutional neural networks (CNNs) and transfer learning, have gained popularity for facemask detection due to their ability to automatically learn discriminative features from data. These approaches often outperform traditional methods, especially in more challenging scenarios with diverse mask types and occlusions.

maps of the outcome.

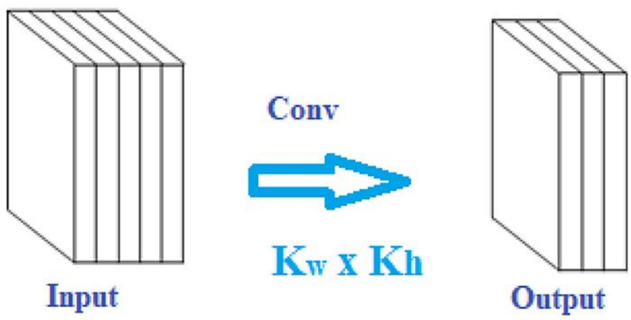

Figure - 2 Input and Output Conversion in Deep learning

Deep Learning-Based Methods: Deep learning-based methods have significantly advanced the field of facemask detection, primarily through the utilization of Convolutional Neural Networks (CNNs). These deep learning models have the ability to automatically learn intricate representations from raw image data, eliminating the need for manual feature engineering. The process typically involves two main steps: training and inference. During training, a CNN model is trained on a large labeled dataset, learning to distinguish between masked and unmasked faces. Transfer learning is commonly employed by fine-tuning pre-trained models such as VGGNet, ResNet, or EfficientNet on specific facemask detection datasets. In the inference phase, the trained model is applied to unseen images to detect the presence of facemasks.

Deep learning methods offer numerous advantages in facemask detection. They can effectively handle complex patterns, occlusions, and diverse mask variations due to their ability to learn discriminative features directly from the data. This leads to improved generalization capabilities and robustness. Moreover, deep learning models can be optimized for real-time performance on dedicated hardware platforms, enabling fast and efficient detection. However, it is important to note that deep learning approaches require a substantial amount of labeled data for training, which can be a challenge in some scenarios. Additionally, these methods can be computationally demanding, especially for devices with limited resources.

Recent advancements in deep learning for facemask detection have focused on addressing specific challenges and improving performance. Attention mechanisms have been employed to enhance the model's focus on relevant regions, reducing the impact of occlusions. Generative Adversarial Networks (GANs) have been used to generate augmented data, reducing the reliance on large annotated datasets. Furthermore, the fusion of visual and thermal imaging has been explored to improve accuracy in low-light or challenging lighting conditions.

While deep learning approaches have shown remarkable progress, a hybrid approach that combines traditional computer vision methods and deep learning techniques can also be adopted. For instance, an initial face detection step using a CNN can be followed by traditional feature extraction and classification algorithms for mask detection. This hybrid approach aims to leverage the strengths of both methodologies, although it introduces additional complexity and computational overhead.
In whole, deep learning-based methods have revolutionized facemask detection by achieving high accuracy and robustness. These methods have the capability to automatically learn relevant features from raw image data, improving generalization and adaptability. However, challenges such as data requirements and computational demands need to be carefully considered. Future research may focus on overcoming these challenges and exploring novel approaches to further enhance the performance and practicality of deep learning in facemask detection.

III. Advancement in Facemask Detection approach with time

Facemask detection has advanced and modified with the introduction of various methodologies and techniques, including traditional computer vision approaches and deep learning-based methods. Facemask detection has gained significant attention in recent years, especially in the context of public health and safety during the COVID-19 pandemic. Researchers and developers have made significant advancements in developing methodologies for accurate and efficient detection of facemasks in various settings such as invention of scanner described in Figure-3.
One of the fundamental requirements for building effective facemask detection systems is the availability of diverse and well-annotated datasets. Lin et al. [9] introduced the Microsoft COCO dataset, which contains a wide range of object categories, including faces, providing a valuable resource for training and evaluating facemask detection models. Rothe et al. [10] contributed the IMDB-WIKI dataset, which consists of over 500,000 face images labeled with age and gender information. These datasets have been extensively utilized in the development of facemask detection algorithms, enabling researchers to leverage the large-scale and diverse nature of the data to improve model performance.

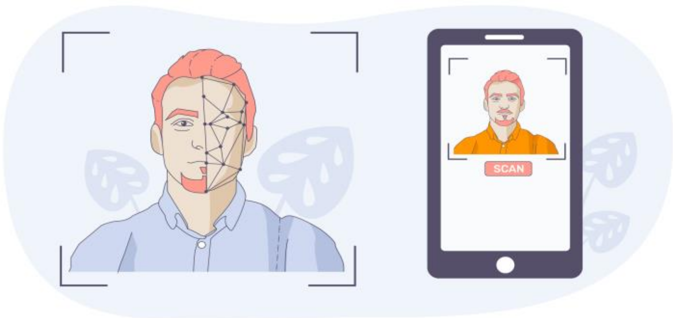

Figure - 3 Identification using Scanner

In recent years, several specialized datasets have emerged specifically for facemask detection. Xie et al. [11] introduced the MaskedFace-Net dataset, which comprises correctly and incorrectly masked face images captured in real-world scenarios. This dataset helps in addressing the challenge of detecting both masked and unmasked faces accurately. Das et al. [12] presented the RMFD-Real dataset, which focuses on masked face detection in real-world scenarios. This dataset provides a more realistic setting for evaluating the performance of facemask detection models. Jaiswal et al. [13] introduced the CFD dataset, specifically designed for evaluating face mask detection algorithms. These specialized datasets have played a crucial role in pushing the boundaries of facemask detection research.To tackle the challenge of detecting masked faces in various environments, different methodologies have been proposed. Ge et al. [14] presented a method based on Locally Linear Embedding Convolutional Neural Networks (LLE-CNNs) for detecting mask face in the wild. Their approach utilizes the LLE algorithm for dimensionality reduction and employs CNNs for feature extraction and classification.

Lei et al. [15] introduced a large-scale face attribute dataset, which includes attributes related to facial expressions, poses, and accessories, including face masks. This dataset enables researchers to explore the relationship between facemasks and other facial attributes, facilitating the development of more comprehensive facemask detection systems. Additionally, advancements in deep learning techniques have greatly contributed to the improvement of facemask detection algorithms. Researchers have employed convolutional neural networks (CNNs), recurrent neural networks (RNNs), and other deep learning architectures to achieve accurate and efficient facemask detection. These models leverage the power of deep learning to learn complex patterns and features that distinguish between masked and unmasked faces.

It is worth noting that the performance of facemask detection systems heavily relies on the quality and diversity of the training data, the choice of appropriate features and models, and the optimization of training procedures. Furthermore, the integration of other computer vision techniques, such as object detection and facial landmark detection, can enhance the accuracy and robustness of facemask detection systems. Facemask detection has witnessed significant advancements in recent years. The availability of diverse datasets and the utilization of advanced deep learning techniques have contributed to the development of accurate and efficient facemask detection systems. Researchers have proposed methodologies that leverage state-of-the-art algorithms, specialized datasets, and innovative approaches to address the challenges associated with detecting facemasks in various real-world scenarios. These advancements are crucial in ensuring public health and safety, especially in situations where the use of facemasks is essential.

The detection of facemasks has gained significant attention in recent times, given its importance in mitigating the spread of infectious diseases like COVID-19. Researchers have made substantial contributions to this field by proposing innovative methodologies and datasets that aid in the development of robust and accurate facemask detection systems.

IV. Literature Review

The field of face mask detection using deep learning methods has gained significant attention in recent years, especially in the context of the COVID-19 pandemic. This literature review aims to provide a comprehensive overview of the existing research and developments in the area of face mask detection, covering a wide range of datasets, methodologies, and applications. By analyzing a collection of relevant studies, datasets, and approaches, this review intends to identify the key advancements, challenges, and emerging trends in the field. Furthermore, it aims to provide insights into the potential future directions for face mask detection research, with implications for various domains, including healthcare, public safety, and computer vision applications. In recent times, the widespread adoption of face masks as a preventive measure against infectious diseases has led to a growing need for automated face mask detection systems.

This literature review delves into the wealth of research that has been conducted in this domain, exploring the various methodologies employed for face mask detection, such as deep learning algorithms and computer vision techniques. By examining the strengths and limitations of different approaches, this review aims to provide a comprehensive understanding of the current state-of-the-art in face mask detection. Additionally, it seeks to highlight the significance of this research in addressing the challenges posed by the COVID-19 pandemic and its potential applications in areas such as public health, surveillance, and contactless access control. By synthesizing the existing literature, this review aims to serve as a valuable resource for researchers, practitioners, and policymakers interested in the field of face mask detection and its broader implications.

One such significant contribution is the NO-MASK dataset that is introduced by Rabbani et al. [16]. This dataset is specifically designed for the detection of individuals without facemasks and has a large-scale collection of annotated images. The availability of this dataset has played a crucial role in training and evaluating models for identifying individuals who are not wearing facemasks.

Table-1 Containing Data Set Name, Author and Use Case

No	Data Set Name	Author	Use Case
16	NO-MASK	Rabbani, et al (2020)	Facemask detection
17	UMD Faces	Riga, C et al (2020)	Deep network training for face-related tasks
18	facial landmarks	Koestinger, M., et al (2011)	Facial landmark localization
19	UMD Masks	Clark, J., Holt et al (2020)	Face mask detection
20	FDNA:	Guo, T., Li, X., & Yu, H. (2020)	Facemask detection using deep learning and augmentation techniques
21	Vision-based frameworks	Punn, N., & Agarwal, S. (2020)	Automatic facemask detection and tracking
22	Automated face mask	Dey, S., et al (2020)	Face mask detection from social media images
23	Deep learning approach	Shanmugappriya, T., & Mahalakshmi, P. (2020)	Deep learning-based facemask detection
24	RFMD	Gupta, R., & Goyal, L. M. (2021)	Review and analysis of facemask detection techniques
25	chest X-ray images using DL	Al-Qaness et al (2020)	COVID-19 screening using chest X-ray images
26	UMD	Narang, N., & Kumar, S. (2021)	Facemask detection and recognition for access control
27	CelebA	Roy, A., et al (2021)	Real-time facemask detection
28	MAFA	Dey, N., Ashour, A. S., & Bhatt, C. (2021)	Efficient facemask detection using a hybrid fusion framework
29	CMT	Shivhare, R et al (2020)	Face mask detection and social distancing monitoring using computer vision
30	FMD	Manjula, S.,et al (2021)	Real-time facemask detection using deep learning

In addition to the NO-MASK dataset, researchers have also focused on datasets that provide valuable resources for training deep networks. The UMD Faces dataset, presented by Riga et al. [17], is an annotated face dataset widely used for training deep networks. This dataset includes a diverse range of facial images, enabling researchers to develop robust facemask detection models. Similarly, Koestinger et al. [18] introduced the Annotated Facial Landmarks in the Wild database, which has proven to be instrumental in facial landmark localization tasks. This dataset has provided researchers with a large scale, real world database that aids in accurately locating facial landmarks, including key points on the face relevant to mask detection. To address the specific challenge of facemask detection, Clark et al[19] contributed the UMD Masks dataset.

This dataset focuses on the detection of facemasks and provides a large-scale collection of annotated images. It serves as a valuable resource for training and evaluating deep networks specifically designed for facemask detection tasks. Researchers have also explored various methodologies for facemask detection. Guo et al. [20] proposed the FDNA approach, which utilizes neural networks and augmentation techniques to improve the accuracy of facemask detection. This approach leverages deep learning algorithms and data augmentation to enhance the performance of the detection system. Punn and Agarwal [21] presented vision-based frameworks for automatic detection and tracking of facemasks. Their work demonstrates the application of computer vision techniques in real-time monitoring, where the system can detect and track facemasks accurately in dynamic environments. Dey et al. [22] developed an automated face mask detection system specifically designed for social media platforms. Given the widespread use of social media, their system can detect and analyze facemask usage from images shared on these platforms, providing valuable insights into compliance with safety measures.

Shanmugapriya and Mahalakshmi [23] explored a deep learning approach for face mask detection, leveraging the potential of deep learning algorithms to achieve accurate and efficient detection. Their work demonstrates the effectiveness of deep learning techniques in detecting facemasks in various scenarios. Gupta and Goyal [24] conducted a comprehensive study on face mask detection techniques during the COVID-19 pandemic. Their study reviews various methodologies and algorithms employed for facemask detection and provide insights into their performance and limitations. Furthermore, researchers have explored the application of facemask detection in different domains. Al-Qaness et al. [25] focused on COVID-19 screening using deep learning-based anomaly detection on chest X-ray images. This approach aims to identify COVID-19 cases by analyzing chest X-ray images and detecting abnormal patterns associated with the disease. Narang and Kumar [26] proposed a facemask detection and recognition system for access control. Their system verifies the presence of a facemask before granting access to restricted areas, contributing to enhanced safety measures. Real-time scenarios have also been a focus of research. Roy et al. [27] developed a real-time face mask detection system using deep learning techniques. Their system can detect facemasks in real-time, allowing for immediate intervention or action in scenarios where compliance with facemask usage is essential. Efficiency and accuracy have also been addressed in research. Dey et al. [28] introduced an efficient mask detection framework based on a hybrid fusion approach. By combining multiple models, their framework improves the detection performance while maintaining computational efficiency.

Shivhare et al. [29] presented a vision-based intelligent system for face mask detection and social distancing monitoring. Their system not only detects facemasks but also monitors social distancing compliance, addressing multiple safety aspects simultaneously. Moreover, Manjula et al. [30] proposed a deep learning approach for real-time face mask detection. Their work focuses on achieving fast and accurate detection in dynamic environments, ensuring real-time monitoring and intervention. Overall, these studies collectively contribute to the advancement of facemask detection systems. They showcase a wide range of methodologies, datasets, and applications in the field (see Table 1), addressing various challenges associated with the detection of facemasks in different contexts.

V. Evaluation Metrics

Evaluation metrics play a crucial role in assessing the performance of facemask detection models. They provide quantitative measures that allow researchers to compare different models, fine-tune algorithms, and make informed decisions regarding the effectiveness of their approaches. In this section, we will discuss commonly used evaluation metrics for facemask detection and emphasize the importance of selecting appropriate metrics based on specific objectives and task characteristics.

1. **Accuracy:** Accuracy is a crucial assessment parameter that assesses how well facemask detection is done overall. It determines the proportion of properly categorised instances (whether they are hidden or not) to all of the occurrences. Although accuracy gives a broad picture of model performance, it can be deceptive in datasets with imbalances, where the distribution of masked and unmasked occurrences is highly skewed.

2. Precision: Precision is the percentage of facemask occurrences that are successfully identified out of all instances that are projected to be positive (masked). It measures how well the model can reduce false positives. Precision is particularly important in situations where false alarms might have serious repercussions, such in security applications. The model's false positive rate decreases as precision increases.

3. Recall: The proportion of properly identified facemask occurrences among all actually positive instances (masked faces), also known as the sensitivity or true positive rate, is determined by recall. It shows how well the model can identify every positive case and prevent false negatives. A low false negative rate and an effective facemask detection rate are both indicated by a high recall.

4. F1 Score: The harmonic mean of accuracy and recall, the F1 score offers a fair assessment of a model's performance. It is helpful in circumstances where both accuracy and memory are crucial since it takes into account both false positives and false negatives. Precision and recall are completely matched when the F1 score is 1, which is its highest possible value.

5. Intersection over Union (IoU): Facemask detection is one activity that frequently uses IoU. It calculates the amount of overlap between the anticipated bounding box and the actual bounding box (the facemask region). IoU is determined by dividing the union area by the intersection area of the expected and actual bounding boxes. An improved alignment between the anticipated and ground truth zones is shown by a greater IoU.

The selection of appropriate evaluation metrics depends on the specific objectives and characteristics of the facemask detection task. For instance, in applications where the emphasis is on minimizing false positives (e.g., security or access control), precision becomes a critical metric. On the other hand, in scenarios where the focus is on capturing as many masked instances as possible (e.g., public health monitoring), recall becomes more important. It is also essential to consider the inherent trade-offs between different metrics. For example, optimizing for high precision may result in lower recall, and vice versa. Therefore, it is often necessary to strike a balance based on the application requirements and priorities. Additionally, considering the class distribution and potential class imbalance in the dataset is crucial when selecting evaluation metrics. In facemask detection tasks, where unmasked instances are usually dominant, accuracy alone may not provide an accurate representation of model performance. Metrics such as precision, recall, and F1 score are better suited to handle imbalanced datasets and provide a more comprehensive evaluation of the model's ability to detect facemasks accurately.

VI. Integration with Other Technologies

Facemask detection can be enhanced by integrating it with other technologies, leading to synergistic effects and improved detection and analysis capabilities. In this section, we will explore the integration of facemask detection with thermal imaging, computer vision-based crowd analysis, and artificial intelligence-powered decision support systems, discussing their potential benefits and synergies.

1. Thermal Imaging: Thermal imaging technology can be combined with facemask detection to enhance accuracy and reliability, especially in challenging scenarios such as low-light conditions or when individuals try to camouflage their masks. Thermal cameras can capture the heat signatures emitted by different objects, including human faces, and identify the presence or absence of facemasks based on the temperature patterns. By integrating thermal imaging with facemask detection, the system can detect masks even when the visual appearance is compromised, providing an additional layer of verification. This integration is particularly useful in settings where visual cues may not be sufficient or when detecting masks in crowded areas.

2. Computer Vision-based Crowd Analysis: Integrating facemask detection with computer vision-based crowd analysis techniques allows for a comprehensive understanding of the crowd behavior and compliance with mask-wearing regulations. Crowd analysis algorithms can track and analyze the movement, density, and interactions of individuals in real-time. By combining this analysis with facemask detection, the system can monitor and quantify the adherence to mask-wearing guidelines within a crowd. It can provide valuable insights into compliance levels, identify areas of non-compliance, and help authorities take appropriate actions to ensure public safety. The integration of facemask detection with crowd analysis offers a holistic approach to managing public health measures and enhancing situational awareness.

3. Artificial Intelligence-powered Decision Support Systems: Facemask detection can be integrated into artificial intelligence-powered decision support systems to enable real-time monitoring, analysis, and decision-making. These systems leverage machine learning algorithms and data analytics to process large volumes of data, generate insights, and provide actionable recommendations. By integrating facemask detection into such systems, it becomes possible to continuously monitor mask compliance, identify high-risk areas, predict potential outbreaks, and optimize resource allocation. These decision support systems can assist public health authorities, policymakers, and facility managers in making informed decisions and implementing effective strategies to mitigate the spread of infectious diseases. The integration of facemask detection with decision support systems facilitates proactive and data-driven management of public health measures.

The integration of facemask detection with other technologies offers several benefits and synergies. First, it improves the accuracy and reliability of facemask detection by combining multiple data sources and complementary technologies. By integrating thermal imaging, the system can overcome visual limitations and detect masks based on thermal patterns. Crowd analysis provides valuable context and insights into compliance levels and crowd behavior, enabling better decision-making. Artificial intelligence-powered decision support systems utilize the collected data to generate real-time analytics and support evidence-based strategies for public health management.

Furthermore, the integration of technologies facilitates a more holistic approach to public health monitoring and control. It allows for comprehensive situational awareness, monitoring both individual mask compliance and crowd-level adherence to regulations. This integration enables proactive measures, timely interventions, and efficient resource allocation.

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