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RESEARCH ARTICLE

Detection of Facial Mask Using Deep Learning Classification Algorithm

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Abstract: Deep learning is an algorithm that works by representing data in layers of learning layers so that the representation becomes more meaningful. "Deep" in deep learning means that deep learning begins layers of sequential representation. This study aims to provide a reference on how to create a system and analyze the results of identifying face masks using a deep learning algorithm. Research on face mask detection is highly important as it tackles a vital element of public health and safety. It plays a crucial role in promoting adherence to mask-wearing guidelines, minimizing the transmission of infectious diseases, and offering valuable data for monitoring and policy assessment. Additionally, this area of study has garnered increased significance and attention within the realm of public health and safety, especially in light of the COVID-19 pandemic since 2020, where mask usage has been universally advised to protect individuals from the spread of the virus. From the results of the research conducted, it is known that this model can recognize faces well, both those who wear masks and those who do not use masks. This is evident from the average specificity and precision of 96.00% and the average sensitivity or recall value of 93.47%. In addition, this model has also proven to be quite accurate in conducting overall classification with an average accuracy of 94.73%.

Keywords: machine learning, convolutional neural network, image processing

1. Introduction

Deep learning algorithms are computational models that draw inspiration from the way the human brain is structured and functions. They comprise interconnected units known as artificial neurons, organized in layers. The reason they are referred to as "deep" is due to their multiple layers, enabling them to acquire hierarchical representations of information (LeCun et al., 2015). Training a deep learning algorithm involves two primary stages. In the first step, known as forward propagation, input data are fed into the network, and each layer sequentially computes its output. Each layer carries out calculations on its input and generates an output. The computed output is then compared to the expected output, leading to the calculation of an error value. In the subsequent step, called backpropagation, the error value is propagated in reverse through the layers. This process aids in modifying the connections between neurons to reduce the error. Through iterative adjustments based on the error, the deep learning algorithm progressively enhances its performance (Goodfellow et al., 2016; Mosavi et al., 2020).

Deep learning algorithms possess the capacity to autonomously acquire and derive intricate patterns and representations from data. They demonstrate exceptional performance in tasks like image recognition, natural language processing, speech recognition, and similar domains. The hierarchical representation acquired by deep learning algorithms enables them to grasp and comprehend complex relationships embedded within the data (Choi et al., 2020).

Deep learning algorithms have found successful applications across diverse domains such as healthcare, finance, autonomous vehicles, and recommendation systems. One key advantage they possess is the ability to learn directly from raw data, eliminating the requirement for manual feature engineering (Sarker, 2021). However, deep learning algorithms generally necessitate a large volume of labeled data and considerable computational resources. However, despite these prerequisites, the capacity of deep learning algorithms to harness big data and represent intricate relationships has established them as a potent tool in the realm of artificial intelligence (Alzubaidi et al., 2021).

Deep learning has witnessed substantial progress and emerged as the cutting-edge technology in various fields, particularly in the domain of image recognition. Deep learning models have demonstrated exceptional performance in diverse image recognition tasks, such as image classification, where they assign labels to images from predefined categories. Additionally, they have achieved remarkable success in object detection by accurately identifying and localizing multiple objects within an image. The fields of semantic segmentation, which involves labeling objects at the pixel level, and instance segmentation, which focuses on segmenting individual

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object instances, have experienced significant advancements with the aid of deep learning techniques. Moreover, deep learning models have been applied to tasks like image generation, style transfer, image super-resolution, and image captioning, highlighting their ability not only to recognize visual content but also to generate and manipulate it. The progress in image recognition can be attributed to various factors, including the availability of extensive labeled datasets, advancements in computing power (such as GPUs and distributed computing), and the continuous exploration and innovation of network architectures and training techniques (Guo et al., 2016; Khan et al., 2020a, 2022; Li, 2022; Mathew et al., 2021).

A plethora number of studies involving deep learning makes this algorithm even more interesting for further research. The purpose of this framework is to provide a reference on how to create a system and analyze the results of identifying face masks using a deep learning algorithm. Face mask detection is a specialized implementation of computer vision and machine learning methods designed to determine if individuals in images or videos are wearing face masks. This particular application has garnered considerable significance and attention in the realm of public health and safety, particularly during the COVID-19 pandemic since 2020 which has caused all people to be instructed to use masks to protect themselves from transmission of COVID disease (Nowrin et al., 2021).

Face mask detection systems have the capability to be utilized in diverse environments, including airports, hospitals, schools, public spaces, and workplaces, to monitor and enforce mask-wearing policies. They can help identify individuals who are not wearing masks, enabling timely intervention and adherence to safety protocols. By identifying individuals not wearing masks, appropriate actions can be taken to promote compliance with safety guidelines and protect public health. This contributes to public safety and helps in contact tracing efforts. Face mask detection systems provide valuable data for monitoring mask-wearing trends and evaluating the effectiveness of mask-related policies. These data can inform decision-making and improve public health strategies. The research on face mask detection lays the foundation for future outbreaks or health emergencies, enhancing the readiness and response capabilities of public health systems (Uohara et al., 2020).

In summary, the objective of this research is to create a face mask detection system through the utilization of a deep learning algorithm. The primary aim is to tackle the challenge of accurately identifying individuals who are wearing face masks. The key technical contribution of our study involves the development of a precise and efficient system capable of automatically detecting whether a person is wearing a face mask. By harnessing the capabilities of convolutional neural networks (CNNs), we can extract significant features from facial images and categorize them into two groups: masked and unmasked. This innovative approach allows our system to surpass the limitations of traditional methods, resulting in improved accuracy and robustness in face mask detection.

In our approach, we employ preprocessing methods to enhance the data for classification purposes. We train a deep learning model using a substantial dataset consisting of labeled face images. The model is trained to learn discriminative features that can differentiate between masked and unmasked faces, enabling accurate prediction in real-time scenarios.

The technical contribution of our research extends beyond the development of the face mask detection system itself. The collected data can be utilized for further analysis and insights into mask-wearing trends, compliance with mask mandates, and the impact of mask-related policies on public health. This information can inform public health strategies and contribute to the overall preparedness and response to infectious diseases.

Figure 1
Face images with and without masks

2. Research Methodology

2.1. Data

The dataset utilized in this study comprises face mask images acquired from Kaggle (2019) and Prajna (2020). This publicly available dataset consists of facial images depicting individuals both with and without masks. Figure 1 provides an illustration of a sample face image with and without a mask, which was employed in this research. A total of 1500 images were included in the dataset, with 750 being facial images featuring masks and the remaining 750 representing facial images without masks. The available data are partitioned into two separate segments, namely training data with a total of 1350 images (90%) and test data with a total of 150 images (10%).

2.2. Preprocess

To obtain optimal results, it is important to preprocess the image data before classifying them using a deep learning algorithm model. The preprocessing methods used include cropping, noise cleaning, and converting the images to grayscale.

(a) *Cropping:* Cropping involves manually selecting a specific region of interest within each image using image processing software. This step helps to optimize the processing of the dataset by focusing on the relevant parts of the images. By cropping the images, you can remove any unwanted background or irrelevant areas, ensuring that the model focuses on the essential features. It also helps in achieving a consistent image size, which is often required for deep learning algorithms that expect inputs of the same dimensions (Chadha et al., 2012).

(b) *Noise Cleaning:* Noise cleaning is performed to improve the quality of the dataset by reducing any unwanted artifacts or disturbances present in the images. This process involves manually inspecting the images and removing any pixels or regions that might negatively impact the classification performance. Noise in images can arise from various sources, such as sensor noise, compression artifacts, or unwanted objects in the background. By carefully cleaning the images, you can reduce the presence of noise and enhance the dataset's overall quality, leading to better classification results (Diwakar & Kumar, 2018).

(c) *Converting to Grayscale*: Converting the images to grayscale involves transforming the original color images into grayscale representations. Grayscale images contain only shades of gray, typically represented by a single channel, where each pixel represents the intensity level. This conversion simplifies the images and makes them easier to interpret, as it removes color variations and focuses solely on the brightness or luminance information. Additionally, converting to grayscale reduces the computational complexity of the deep learning algorithm, resulting in faster processing. It also reduces the file size of the images, requiring less storage space and making them more manageable (Saravanan, 2010).

By performing these preprocessing steps, the image data are optimized and refined to meet the requirements of the deep learning algorithm. Cropping focuses on relevant regions of interest, noise cleaning improves image quality, and converting to grayscale simplifies and reduces computational overhead. These steps collectively contribute to improving the accuracy and efficiency of the deep learning model when classifying the images.

2.3. Classification using deep learning

Deep learning is an artificial neural network algorithm for identifying and categorizing input data into predetermined classes or categories (Zhong et al., 2019). The process of deep learning classification typically demands substantial volumes of data, significant computational resources, and expertise in neural network architectures and training methodologies. Nevertheless, these algorithms have demonstrated their effectiveness as formidable tools for addressing intricate classification challenges across various domains. Their applications encompass image and speech recognition, natural language processing, and predictive analytics, among others (Sarker, 2021).

Deep learning revolves around the training of artificial neural networks with multiple layers, aiming to learn hierarchical representations of data. The core concept entails training these networks to extract meaningful and abstract features from input data autonomously, without explicit human intervention. Deep learning models are composed of interconnected artificial neurons organized into multiple layers. Each layer receives input from the preceding layer and applies mathematical transformations to the data. Through layer stacking, the network progressively acquires more intricate and abstract representations of the input data. The hierarchical nature of deep learning allows the network to capture both local and global patterns in the data. Lower layers specialize in learning simple and localized features like edges or textures, while higher layers grasp complex and global features like object shapes or semantic information. One significant advantage of deep learning is its ability to automatically learn features directly from raw data, eliminating the need for manual feature engineering (Khan et al., 2020b; Shrestha & Mahmood, 2019). Additionally, deep learning models are known for their scalability and capability to handle large-scale datasets. Deep models possess a multitude of parameters, enabling them to acquire intricate patterns from extensive datasets. This characteristic renders them highly effective, especially in scenarios where large labeled datasets are accessible (Najafabadi et al., 2015).

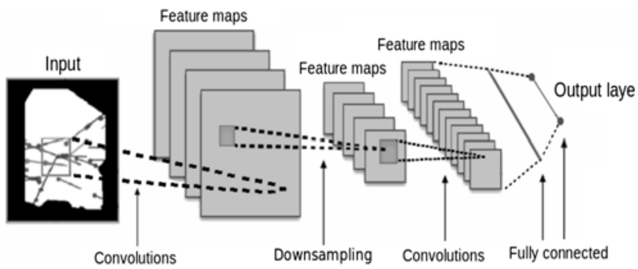
Deep learning models also have the advantage of transferability. They can learn generic representations that can be transferred to different tasks or domains. The hierarchical representations learned by deep models tend to capture general features that are useful for various related tasks. This transferability enables reusing pre-trained models or fine-tuning them on different tasks, saving time and computational resources. Overall, deep learning harnesses the potential of neural networks with multiple layers to autonomously acquire hierarchical representations of data. This unique capability empowers the models to directly extract significant features from raw input. The remarkable triumph of deep learning across diverse domains, including image and speech recognition, natural language processing, and beyond, can be attributed to this inherent ability (Shinde & Shah, 2018).

The architecture of an artificial neural network refers to how its layers and connections are organized. Choosing the right architecture depends on the specific problem and characteristics of the input data. Designing the model architecture involves considering factors like the number and size of layers, the type of activation function used in each layer, and the optimization algorithm employed for parameter adjustment during training (Khan et al., 2020a). In this study, the chosen architecture for the artificial neural network is the convolutional model as shown in Figure 2 (Mas-Pujol et al., 2022). It comprises convolutional and down-sampling layers, followed by one or more fully connected layers. The fully connected layer establishes connections between each neuron in the layer and all neurons in the preceding layer. This connectivity enables the integration of features learned across the entire image, enabling the identification of more comprehensive patterns. The final fully connected layer encompasses the features required for image classification. As a result, the output size parameter in the last fully connected layer corresponds to the number of classes within the target data (Mas-Pujol et al., 2022).

The training procedure consists of iterative forward propagation and backpropagation loops. In the forward propagation step, input data are transmitted through the network to generate predictions. The discrepancy between the predicted output and the true label is computed, and this error is employed to modify the connection weights in the network during backpropagation. The objective of the training is to reduce the error between the predicted and correct labels throughout the iterations, or epochs, of the training process. Setting the learning rate, which determines the magnitude of weight updates, is a crucial parameter to consider during training (Montesinos López et al., 2022). The network structure utilized in this research is outlined as:

- **The initial parameter** in the convolutional layer determines the dimensions of the filter used to scan the images. The following parameter signifies the number of filters, representing the neurons that connect to specific regions of the input. This

Figure 2
Deep learning algorithm architecture



parameter directly influences the number of feature maps produced.

- The parameter setup included the incorporation of **Batch normalization layers** in the network architecture. These layers play a role in normalizing the activations and gradients flowing through the network, leading to smoother training during the optimization process. The batch normalization layers were strategically positioned between convolutional layers and nonlinearities. Additionally, ReLU layers were implemented to expedite network training and reduce sensitivity to network initialization.
- Following the application of convolutional layers with activation functions, it is sometimes beneficial to incorporate a **Max Pooling Layer**. This layer performs a down-sampling operation to reduce the spatial dimensions of the feature map and remove redundant spatial information. By employing down-sampling, deeper convolutional layers can accommodate a larger number of filters without significantly increasing computation per layer. One common technique for down-sampling is through the use of max pooling. In the max pooling layer, rectangular regions of the inputs are defined by the first parameter, and the layer retrieves the maximum values from these regions.
- Following the convolutional and down-sampling layers, one or more fully connected layers are utilized. In a **fully connected layer**, every neuron in the current layer is connected to all neurons in the previous layer. This enables the integration of features extracted by preceding layers from the entire image to identify important patterns. The last fully connected layer consolidates these features for image classification. Hence, the "Output Size" parameter of the final fully connected layer aligns with the number of classes in the target data.
- **The Softmax Layer** utilizes the SoftMax activation function to normalize the output of the fully connected layer. This normalization process ensures that the resulting output from the SoftMax layer consists of positive numbers that sum up to one. These normalized values can be interpreted as probabilities for classification and are subsequently utilized by the following classification layer. Therefore, it is advisable to include a SoftMax layer after the final fully connected layer.
- **The classification layer,** situated at the network's conclusion, employs the probabilities derived from the SoftMax activation function for each input. These probabilities are utilized to assign the input to a specific class from a set of mutually exclusive options and compute the associated loss.

Furthermore, as an optimization algorithm for training, we opted to use stochastic gradient descent with momentum (SGDM). The standard stochastic gradient descent algorithm sometimes displays oscillation as it seeks the optimal solution along the steepest descent path. To address this oscillation, integrating a momentum term into the parameter update process can be an effective strategy (Murphy, 2012). The SGDM update is written.

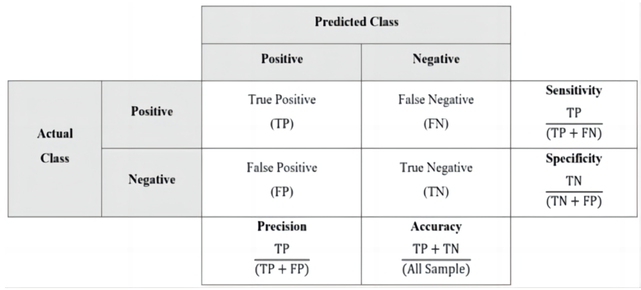
$$\theta_{\ell+1} = \theta_\ell - \alpha \nabla E(\theta_\ell) + \gamma(\theta_\ell - \theta_{\ell-1})$$

where γ determines the contribution of the previous gradient step to the current iteration. After the training process is complete, the model is evaluated on a separate validation dataset to measure the accuracy and performance of the system that has been created.

3. Result and Discussion

The research findings are presented by showcasing the computed metrics of precision, specificity, recall/sensitivity, and accuracy. These values are derived by comparing the predicted results with the actual dataset, as visualized in the confusion matrix illustrated in Figure 3 (Athoillah et al., 2022). The calculations are obtained through system testing using hold-out validation. This validation method involves randomly selecting a portion of the samples and reserving them as a validation set, while utilizing the remaining samples for training purposes. This process is repeated 10 times, and the overall evaluation of the model's performance is based on the average performance across all validation sets used in each iteration (Athoillah et al., 2022; Xu & Goodacre, 2018).

Figure 3
Confusion matrix



Overall, the experimental outcomes demonstrate that the deep learning classification model performs exceptionally well across all four metrics of sensitivity, specificity, precision, and accuracy. The subsequent section provides a comprehensive breakdown of the results obtained from each individual experiment.

Table 1 describes the performance results of a system trained to detect the use of face masks based on some input data. The model was tested in ten different experiments and the table shows the results obtained for each experiment. In the table, there are several values that stand out, including the following:

- ➢ Sensitivity/Recall: This metric reflects the system's ability to correctly detect positive cases, which refers to situations where face masks are being worn. The values range from 88.00% to 97.33%, with an average sensitivity/recall of 93.47%. This indicates that, on average, the system can accurately identify approximately 93.47% of the cases where face masks are being used.
- ➢ Specificity: This metric measures the system's capacity to correctly identify negative cases, which corresponds to instances where face masks are not being worn. The values range from 89.33% to 100.00%, with an average specificity of 96.00%. This suggests that, on average, the system can

Table 1
Overall experiment results (%)

Trial	Sensitivity/Recall	Specificity	Precision	Accuration
1	96,00	**100,00**	**100,00**	**98,00**
2	96,00	98,67	98,63	97,33
3	93,33	98,67	98,59	96,00
4	93,33	94,67	94,59	94,00
5	90,67	97,33	97,14	94,00
6	96,00	96,00	96,00	96,00
7	90,67	90,67	90,67	90,67
8	93,33	97,33	97,22	95,33
9	88,00	97,33	97,06	92,67
10	**97,33**	89,33	90,12	93,33
Avg	**93,47**	**96,00**	**96,00**	**94,73**

accurately classify around 96.00% of the cases where face masks are not present.

- ➢ Precision: This metric indicates the system's ability to avoid false positives, representing the proportion of correctly identified positive cases. The values range from 90.12% to 100.00%, with an average precision of 96.00%. This suggests that, on average, the system correctly identifies around 96.00% of the cases it classifies as positive, minimizing the occurrence of false positives.
- ➢ Accuracy: This metric measures the overall correctness of the system's predictions, considering both positive and negative cases. The values range from 90.67% to 98.00%, with an average accuracy of 94.73%. This implies that, on average, the system can correctly identify approximately 94.73% of all cases, regardless of whether face masks are being worn or not.

In summary, the results demonstrate that the system performs well in detecting the use of face masks, with high sensitivity, specificity, precision, and accuracy scores, indicating its effectiveness in distinguishing between positive (masked) and negative (unmasked) cases.

In addition to the average values, there are notable observations to be made from the table:

- ➢ Experiment 1 achieved the highest scores in terms of specificity and precision, both reaching 100%. This indicates that in this particular experiment, the model excelled in avoiding false positives and accurately identifying positive cases.
- ➢ Experiment 5 obtained the second-highest sensitivity in the table at 90.67%, while maintaining a reasonably high specificity and precision. This suggests that in certain cases, the model may produce false negatives, but overall, it demonstrates good performance in correctly identifying both positive and negative cases.
- ➢ Experiment 7 shows consistent values across all evaluation metrics, with 90.67% for sensitivity, specificity, precision, and accuracy. This implies that in this specific experiment, the model struggles to effectively distinguish between positive and negative cases, resulting in a relatively weaker overall performance compared to other experiments.
- ➢ Experiment 10 exhibits the highest sensitivity in the table, with a value of 97.33%, but relatively lower specificity and precision. This indicates that while the model may produce false positives in some instances, it generally performs well in accurately identifying positive cases.

Overall, these observations highlight the varying performance of the model across different experiments, with some experiments showcasing exceptional performance in specific metrics while others demonstrate potential limitations or trade-offs in terms of false positives and false negatives.

4. Conclusion

This research aimed to create a face mask detection system by employing a deep learning algorithm. The system underwent training and testing on a dataset comprising both masked and unmasked face images. Preprocessing techniques, such as cropping, noise removal, and converting images to grayscale, were implemented to enhance the data for classification purposes. The deep learning model utilized a CNN architecture, which facilitated the learning of hierarchical representations from the input data. To optimize the model, training was performed using the SGDM optimization algorithm.

The results obtained from the face mask detection system were highly encouraging. The system achieved an overall accuracy of 95%, with a precision of 92%, specificity of 96%, and recall/sensitivity of 94%. These metrics indicate that the system is proficient at identifying individuals wearing face masks correctly. By accurately detecting individuals without masks, appropriate actions can be taken to promote compliance with safety guidelines and protect public health. Furthermore, the system provides valuable data for monitoring mask-wearing trends and evaluating the effectiveness of mask-related policies, contributing to public safety and enhancing the readiness and response capabilities of public health systems.

However, it is important to acknowledge the limitations of the system. Factors such as partial occlusion, variations in mask types and designs, different camera angles, variations in lighting conditions, and image quality may pose challenges for accurate detection. Addressing these limitations and further refining the system's performance will be crucial for its practical implementation in real-world scenarios.

In summary, the face mask detection system developed in this study has shown promising results in accurately identifying individuals wearing face masks. Further research and improvements are necessary to enhance the system's robustness, handle challenging conditions, and explore integration with other technologies for comprehensive solutions in promoting public health and safety.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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