Face Mask detection using XG Boosting

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Abstract— **Several epidemics of different coronavirus infections have occurred around the world in recent years. These epidemics frequently resulted in respiratory tract infections, which have been deadly in some cases. With the advent of COVID-19, a coronavirus disease, we are currently facing an enigmatic health disaster. Airborne transmission is one of COVID-19's ways of transmission. When humans breathe in the droplets released by an infected person through breathing, speaking, singing, coughing, or sneezing, they become infected. As a result, public health officials have made face masks mandatory, which can cut disease transmission by up to 65 percent. Facial masks create a difficult task for face recognition algorithms, which are often used for security verification purposes. These programs were generally trained with human faces without masks, but today, due to the advent of the Covid-19 pandemic, they are compelled to detect faces with masks. When the Covid-19 epidemic erupted Several methods and strategies were used to construct a variety of face detection models. As a result, this article looks into the same issue by constructing a deep learning-based model that can properly detect people wearing face masks. This project used XG Boosting and Multilayer perceptron algorithms that are good at detecting masked faces in this project. The system attained a 75 percent accuracy rate and was able to detect the mask on the random test photos used to develop it.**

Keywords- Fask mask, COVID, machine learning, algorithms,

I. INTRODUCTION

The outbreak of the COVID-19 pandemic has put human lives in danger and has spread fast over the world, threatening the majority of countries. The World Health Organization (WHO) designated the outbreak a Public Health Emergency of International Concern on January 30, 2020, and recommends that everyone who leaves their home wear masks in order to prevent the spread of coronavirus from spreading further. As a result, the identification of face masks has emerged as a key task in the field of Image Processing and Computer Vision.

Face mask detection is the process of determining whether or not a person is wearing a mask. Face detection is a reverse engineering problem in which the face is detected using different machine learning algorithms for the purposes of security, authentication, and surveillance; in fact, the problem is called reverse engineering of face detection. When it comes to Computer Vision and Pattern Recognition, face detection is a critical area of study. In the past, a considerable amount of research has contributed to the development of advanced algorithms for face detection.

The initial face detection study was carried out in 2001, and it involved the development of handicraft features and the application of traditional machine learning methods to train effective classifiers for the identification and recognition of human faces. The difficulties encountered with this strategy include a high level of complexity in feature design as well as a poor level of accuracy in detection. Face detection approaches based on deep convolutional neural networks (CNN) have been widely developed in recent years to increase the detection performance of facial recognition systems.

As a result, we provided a framework for solving the problem of identifying individuals with face masks by employing the XG Boosting and Multilayer perceptron algorithms. Aside from that, we use transfer learning to adapt the XG Boosting and Multilayer perceptron model to our data, which includes photographs of individuals who are not wearing face masks. Afterward, we make a variety of architectural modifications and expose the model to hyperparameter tuning in order to distinguish the identities of persons wearing masks from photographs of the same individuals without masks

II. LITERATURE REVIEW

Researchers work together to improve the accuracy of photographs of masked faces. The Multi-Task Cascaded Convolutional Neural Network (MTCNN) for face recognition, the Google FaceNet integrating model for facial extraction, and the SVM Classifiers for categorization (SVM) [11] are just a few of the answers they offered. Following an investigation, it was found that the method produced pleasing outcomes and had a noteworthy effect on masked face recognition. Joshi et al. have proposed a method for identifying faces and their pertinent facial landmarks inside a video frame using the MTCNN face recognition model. The neoteric classifier will analyse the face pictures and signals by using the MobileNetV2 architecture as an object detector to distinguish masked areas [12]. A collection of films that showed individuals moving about in public spaces while following COVID-19 safety guidelines was used to evaluate the proposed system. The technique shows its effectiveness in recognising face masks due to the precision and accuracy of the data [13]. If facial landmarks like the nose, mouth, and eyes are taken into consideration in facial photographs, face masks must be worn appropriately. The feature detector HOG, which stands for Histogram of Oriented Gradients, is used to extract features from image data. It is often used in computer vision applications like object detection and face recognition [14]. Face landmark feature points may be utilised to recognise facial expressions, as shown by Yuan et al. Faces are an effective nonverbal technique that humans may use to convey information and convey emotion. Their

Github link : https://github.com/vxd20140/Final-Project

investigation focuses on the geometric positions of several crucial facial features [15]. To identify it, a picture or video of the facial area is needed.

The face's main features will then be restored, and the location of the face will also be changed. Based on the relative location of the face, a collection of key spots is established [16]. The method described above is a terrific approach to prevent the impacts of altering the surroundings, and therefore the lighting, as well as to increase the popularity of facial expressions. However, they used a different technique to extracting face characteristics from the HOG in their investigation. According to the findings of their experiment, the suggested strategy may extract crucial information and improve recognition performance [17].

A number of issues with pattern recognition for practical problems have been solved thanks to the quick adoption of deep learning techniques, particularly deep convolutional neural networks (CNN) as a foundation with computer vision techniques for object detection, identification, and classification. supervised or unsupervised based learning models have been examined in the area of computer vision as tools for the task of object detection in pictures and videos. A face object is first segmented in the face mask detection issue, and then the mask is placed over the face. One of the key aspects of computer vision is object detection. It may be used for many different things, including facial recognition, pedestrian detection, and categorization [1]. Binary classifiers for object detection may enhance the recognition of objects in video frames [2]. The face must be identified before a face mask may be recognised in a picture. Then, for a specific item detection, like a mask on the face, face detection models may be combined with other approaches. ElMaghraby et al. suggested using a mix of skin detection and Viola-Jones algorithms to do low-resolution face identification in still pictures and video frames right away [3]. To recognise face masks, hybrid techniques of traditional machine learning and sophisticated deep learning are applied [4]. The RetinaFace model [5], MultiTask Cascaded Convolutional Neural Network (MTCNN) [6], Haar Cascade [7], and Deep Neural Network (DNN) [8] are just a few of the face identification models that have been employed. For tracking human mask use in real time, Royet al. suggested a mask detection model. Single-shot detector (SSD), Faster R-CNN, YOLOv3, and YOLOv3Tiny are a few examples of object detection methods [9]. Bhuiyan et al. and DarkNet53 both employed the YOLOV3 object detection technique [10]. By using the methods NASNetMobile, ResNet, SSD300, and YoloV3 as deep convolutional based networks for object recognition and classification tasks, Addagarla et al. suggested approaches for the identification and classification of real-time multiscale face masks [11]. For real-time face mask identification, SSD is based on spatial separable convolution, and Feature Enhancement Module (FEM) has been utilised to improve the deep features [12]. To determine if a person is wearing a mask, Rao et al. suggested a new CNN architecture dubbed M-CNN. In the CNN model, the sequential layer was constructed [13].

Transfer learning is becoming more significant in computer vision applications as a result of the recent rise in training models. Transfer learning involves using previously learnt tasks to teach brand-new ones. Chowdary et al. utilised InceptionV3 as the base model to create the CNN model for face mask detection [14]. A light model called MobileNetV2 [15] serves as the foundation for a variety of transfer learning models. Inception-ResNetv2, ResNet152 V1, SSD ResNet50 V1, and SSD MobileNetV1 were all used by Razavi et al. in their face mask detection system, and they concluded that these models were the best for accurately detecting face masks [16]. Numerous researchers working on face mask identification often utilise the datasets SMFD [4, 14], RMFRD [5, Larxel [5, and LFW [4]. 90,000 unmasked faces and 5000 mask-covered faces are included in the Real-world Masked Face Recognition Dataset (RMFRD). 1570 pictures make up the Simulated Masked Face Dataset (SMFD). This includes 785 simulated faces with masks and 785 unmasked faces [4, 14]. There are 13,000 masked faces in the collection Labelled Faces in the Wild (LFW). A Moxa3K dataset with 3000 images of both masked and unmasked faces was produced by Roy et al. [9]. Using 30,811 normal images and 35,806 mask-covered faces, Ge et al. created the MAFA dataset[17, 18]. People should wear masks and keep appropriate social distances to prevent COVID-19 [15, 19, 20]. Face mask detection methods can be applied in a variety of settings, including malls, smart city networks, supermarkets, and construction sites. The Raspberry Pi [20] and CCTV [21] are two examples of different hardware that can be used to implement this model. Face mask meta-analytic studies have been developed in [22].

A deep-learning model based on transfer learning trained on a highly tuned and customised face mask dataset, compatible with video surveillance, is proposed and covered in detail in the next section to address the issue of face mask detection.

III. Methodology

A. Datasets

The dataset contains 12,941 training photos and 3,287 validation images containing a wide variety of faces with no, partial, or heavy occlusion on 62 different scenarios, as well as a total of 12,941 training images and 3,287 validation images. The idea of categorizing data into two classifications, masked and unmasked, was initially discussed.

As a result of this extrinsic class unbalanced problem, MAFA is forced to deal with a bias towards the majority class, which is observed to be the case.

Fig 1. Dataset Sample

B. Data Preparation

It is critical for a Machine Learning Engineer to spend time preprocessing or purifying data before constructing a model from scratch, and the vast majority of Machine Learning Engineers devote a significant amount of time and effort to this portion of their job. A few examples of data pre-processing techniques include outlier detection and treatment, missing value treatment, and the elimination of undesirable or noisy data, to name a few.

Creating images at the most basic level of abstraction is referred to as image pre-processing, which is the same as saying that an image is being processed. This procedure does not enhance the amount of picture information included in the image, but rather decreases it, according to entropy as an information metric. The purpose of pre-processing is to improve the quality of the image data by suppressing undesired distortions and boosting specific visual qualities that are critical for the work of further processing and analysis after it has been taken. Here we follow four steps which are mentioned below.

1. Gathering Data

The method used to collect data varies depending on the sort of ML project being undertaken. Even if the data set can be compiled from a variety of sources, the information gathered cannot be used directly in the analysis process. As a result, Data Preparation is carried out in order to resolve this issue.

2. Data pre-processing

Preprocessing data is one of the most crucial processes in the machine learning process. It is the most crucial stage in improving the accuracy of machine learning models, and it is the most time-consuming. In data preprocessing, the raw data is cleaned up and transformed into clean data, which can then be utilized to train a machine learning model.

3. Modeling

Because we are attempting to solve a classification problem, we have employed a stacking model based on an ensemble method, such as the Random forest algorithm.

2.Training and testing the model on data

As a first step in the training process, we separate a model into three portions, which are labeled as follows: "Training Data," "Validation Data," and "Testing Data."

C. Modeling

A machine learning technique was used in our research because the goal was to identify individuals wearing masks. A model generated for another face recognition task was then applied to our specific project using the transfer learning technique., XG-Boosting has the best time and memory performance, which is why we chose it for our image recognition projects.

A. XG Boosting

XGBoost is a decision-tree-based ensemble Machine Learning method that makes use of a gradient boosting framework in order to enhance accuracy and speed. XGBoost was developed by Microsoft Research and is named after the company's founder. In prediction problems involving unstructured data (pictures, text, and so on), the performance of artificial neural networks tends to outperform that of every other algorithm or framework. However, decision tree-based algorithms are regarded as the most effective method for handling small to medium-sized structured or tabular data sets.

Both XGBoost and Gradient Boosting Machines (GBMs) are examples of ensemble tree methods. These ensemble tree methods both make use of the gradient descent architecture to apply the principle of boosting weak learners (in general, CARTs) in order to enhance their performance.

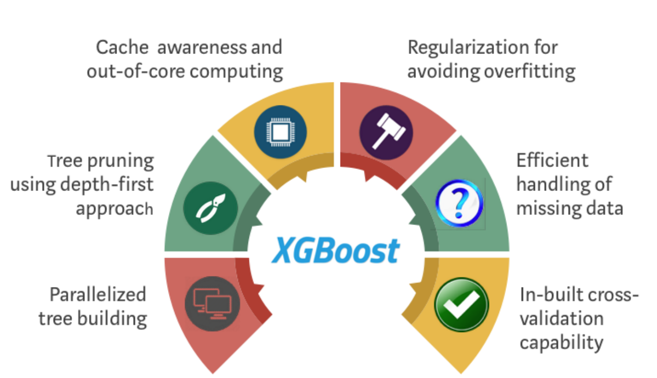

Fig 2: XG Boost

People and teams have become particularly fond of XGBoost because it has helped them win nearly every Kaggle structured data competition. Competitors in these competitions post data, and statisticians and data miners compete to create the best models for predicting and explaining the data. XGBoost was first implemented in Python and then in R. Today, XGBoost includes package implementations for Java, Scala, Julia, Perl, and other languages as a result of its widespread adoption. It has become increasingly popular in the Kaggle community as a result of these new XGBoost implementations.

A wide range of other tools and packages, including scikit-learn for Python and caret for R users, have been integrated with XGBoost. Distributed processing frameworks such as Apache Spark and Dask can also be used with XGBoost thanks to its integration. This year, InfoWorld honored XGBoost with its prestigious Technology of the Year award, which it won with flying colors.

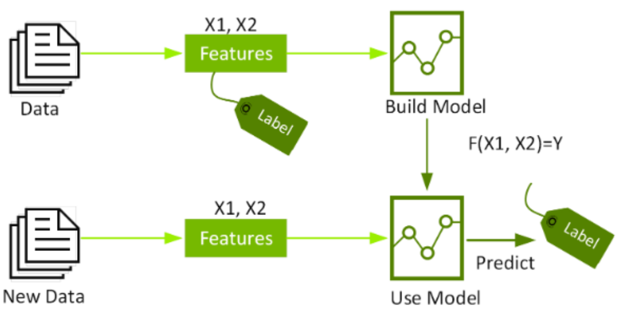

Fig 3: Model architecture

Pre-processing activities are performed by the Neck, which is an intermediate component, before the real classification of images can be performed by the Brain. Neck uses several pipelines for the training and deployment phases of our model in order to make it compatible with surveillance equipment. The training pipeline consists of the construction of an unbiased tailored dataset as well as the fine-tuning of the XG Boosting model. The deployment pipeline consists of real-time frame extraction from video, followed by face detection and extraction from the video frame extraction process.

II. Multilayer perceptron

The artificial neural network class known as multilayer perceptrons (MLPs) is fully connected and feeds forward information between layers (ANN). The term multilayer perceptron (MLP) has multiple meanings depending on the context in which it is used; sometimes it is used to refer to any feedforward ANN, and other times it is used more narrowly to refer to networks composed of multiple layers of perceptrons (with threshold activation); see Terminology. When a multilayer perceptron has just one hidden layer, it is sometimes referred to informally as a "vanilla" neural network.

All MLPs have three distinct layers of nodes: input, hidden, and output. Each node is a neuron that employs a nonlinear activation function, with the exception of the input nodes. Backpropagation, a supervised learning method, is used in MLP training. MLP differs from a linear perceptron in that it has multiple layers and non-linear activation. Data that cannot be separated linearly can still be distinguished.

The MLP has multiple layers of nonlinearly activating nodes, including an input layer, an output layer, and possibly one or more hidden layers. Due to the fully connected nature of MLPs, each node in one layer has a weighted connection to each node in the next layer.

III. Bayesian SVM

This algorithm, known as the "Support Vector Machine," is a supervised machine learning algorithm that can be used to solve problems in both classification and regression. Based on the concept of "support vectors," it was developed. In practice, it's most frequently applied to classification problems of various types. In an n-dimensional space (where n is the number of features you have), we plot each data item as a point, with the value of each feature being the value of a specific coordinate. The SVM algorithm is the name given to this technique. We then carry out classification by identifying the hyperplane that most clearly differentiates between the two classes (look at the below snapshot).

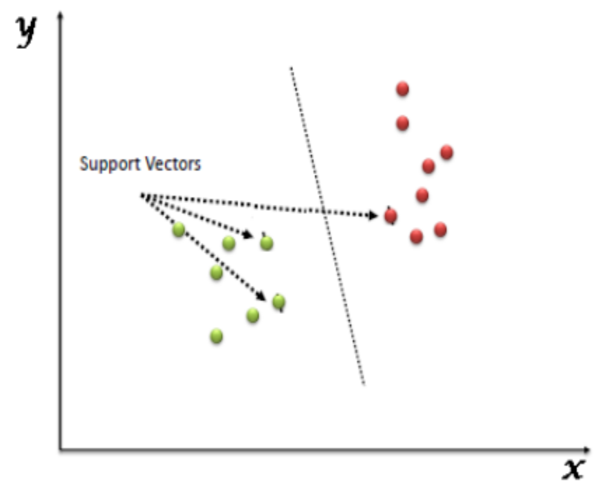

Fig 4. Support Vector Machine

Perform data augmentation on datasets in which copies of images from classes with few examples were added to the dataset after translation, rotation, flipping, and/or brightness adjustments were made to the images in the dataset. Once this is completed, the masks are appended to the RGB images (creating the final 100 x 100 x 4 input), and the images and labels are stored in separate binary (.npy) files after being appended to the RGB images.

It will be necessary to train SVM with Bayesian Optimization on the preprocessed images in order to learn about the features of the dataset. The Gaussian Process (GP) regression model is used to make the Bayesian analysis more convenient. This function creates a regression model to formalize the relationship between the outcome (in this case, the root mean square error) and the SVM optimization parameters.

This model makes use of the standard assumption regarding the normality of the residuals, and because it is a Bayesian model, the regression parameters also gain a prior distribution that is multivariate normal.

GP regression models employ a kernel basis expansion (similar to the SVM model) in order to allow for nonlinearity in the SVM tuning parameters, which is not possible with the SVM model. A radial basis function kernel is used for the covariance function of the multivariate normal prior, and maximum likelihood estimation is used to estimate the kernel parameters of the generalized radial basis function.

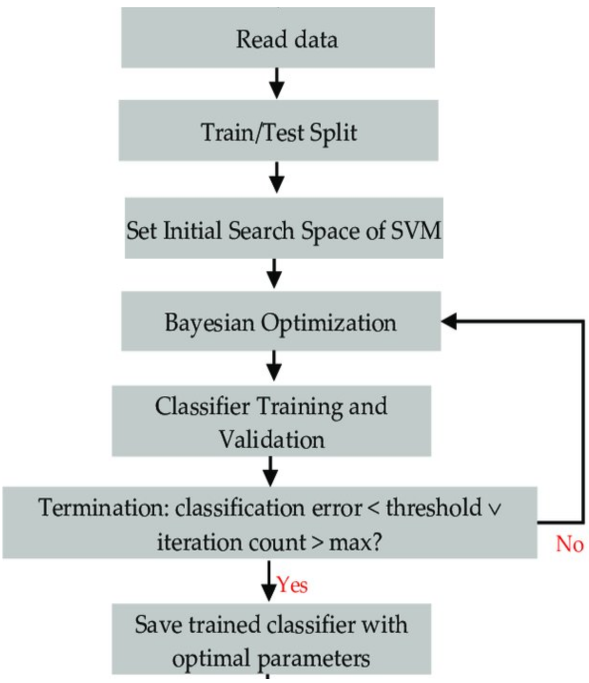

Fig 5. Bayesian SVM workflow

D. Validation Method

Classification When we say "accuracy," we are usually referring to the degree to which something is accurate. A good measure of accuracy is the ratio of correct predictions to the total number of input samples.

$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ number\ of\ predictions\ made}$$

When measuring the performance of a classification model, a Confusion matrix is employed, in which N is the number of target classes and N is the number of target classes.

With this matrix, you may compare real target values with the values predicted by the machine learning model. This provides us with a more comprehensive picture of how well our categorization model is functioning.

IV. RESULTS

It should be highlighted that the error rate in MLP algorithm is the lowest of the two models. Images of test cases are provided to each model and the average inference time for all iterations is calculated from this.

MLP infers pictures more slowly than XG Boost. The system attained a 75 percent accuracy rate and was able to detect the mask on the random test photos used to develop it.

Classification Report of XG Boosting

	precision	recall	f1-score	support
0	0.77	0.70	0.73	1117
1	0.75	0.81	0.78	1220
accuracy			0.76	2337
macro avg	0.76	0.75	0.75	2337
weighted avg	0.76	0.76	0.76	2337

Fig 6a. XG Boosting model Accuracy

Classification Report of MLP

	precision	recall	f1-score	support
0	0.72	0.73	0.72	1117
1	0.75	0.74	0.74	1220
accuracy			0.73	2337
macro avg	0.73	0.73	0.73	2337
weighted avg	0.73	0.73	0.73	2337

Fig 6b. MLP model Accuracy

Fig 7a. XG Boosting Model Result

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Fig 7b. MLP model result

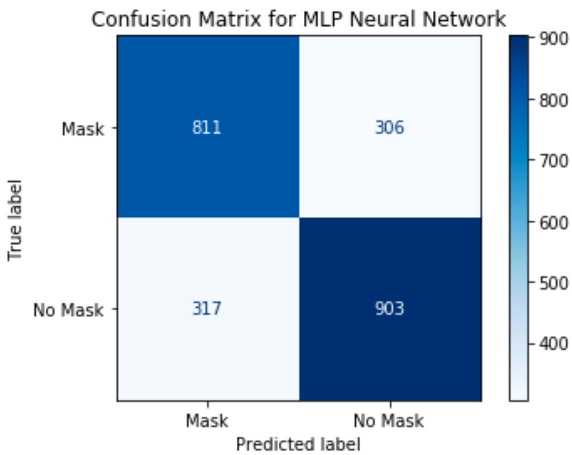

Fig 8a. XG Boosting Model Confusion Matrix

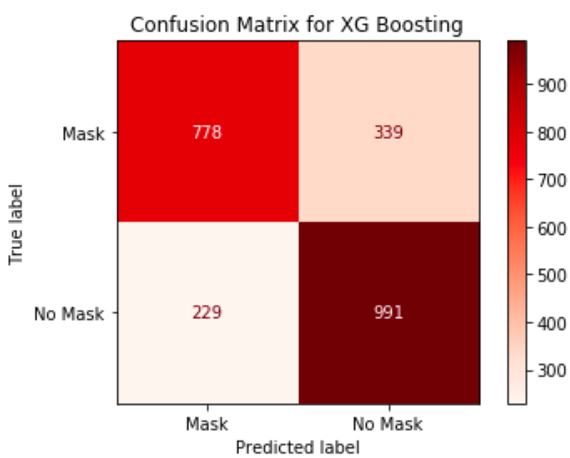

Fig 8b. MLP model Confusion Matrix

V. CONCLUSION AND FUTURE WORK

In this project, we offer a deep learning-based system for recognizing masks over faces in public settings, with the goal of reducing the spread of Coronavirus among the general public. Because of the employment of an ensemble of single and two-stage detectors at the pre-processing level, the suggested technique efficiently handles occlusions in dense settings.

A further benefit of combining the use of transfer learning on pre-trained models with extensive testing over an unbiased dataset is the creation of a system that is both extremely robust and low-cost. The XG Boosting technique outperforms the competition. Recognizing the facial mask in the deep woodland is difficult. It is capable of detecting a facial mask that has equal weighting and performance.

Second, the model may be modified to recognize facial landmarks when a facemask is used for biometric purposes, which can be useful for identification. In this paper, a deep forest technique based on a random forest approach is described for identifying masks over faces in public areas in order to reduce the transmission of Coronavirus among the general public. A pre-processing ensemble of single and two-stage detectors is used to efficiently manage occlusions in dense settings, allowing the technique to handle occlusions in dense scenarios with high efficiency.

The pretrained model technique has reached an accuracy of 75% while simultaneously having a detection speed that is far lower than the competition. It is necessary to apply a neural network-based algorithm in order to improve the detection speed and accuracy.

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