Analysis of selected machine learning algorithms for development of face recognition system for access control in the post COVID-19 era

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Abstract

The mandatory wearing of face masks orchestrated by the COVID-19 pandemic has brought some complexities to the ability of face recognition systems in identifying such faces. Thus, this study examined the performance of some selected machine learning algorithms: Convolutional Neural Network (CNN), Linear discriminant analysis (LDA), Logistic Regression (LR), K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Naïve Bayes (NB) and Decision Tree (DT) for the recognition of masked and unmasked human faces; and developed a face recognition system based on the algorithm with the best performance. The dataset was composed of 11,792 masked and unmasked facial images collected from Kaggle online repository. The set was divided into 70%, 20% and 10% respectively for training, testing and validation each for the masked and the unmasked face images. The images were augmented randomly for training, with some rotated 30 degree, some zoomed 20%, some shifted horizontally by 10% in width, some shifted vertically by 10% in height and some flipped horizontally. The performance analysis of the algorithms presented accuracies of 99% and 99% for the CNN; 93% and 98% for LDA; 93% and 93% for LR; 86% and 78% for the NB; 70% and 70% for the KNN; 64% and 45% for the DT; and 92% and 98% for the SVM respectively for training and cross validation. Overall, the CNN recorded the highest recognition accuracy. Thus, a CNN user-friendly face recognition, system was developed, and tested with a number of real-life human masked and unmasked faces which showed excellent recognition performance. The implementation was carried out with appropriate Python machine libraries. The developed system could be very useful for access control and surveillance. Therefore, this study recommends the adoption of the developed systems for face recognition-based security system.

Keywords: Masked, Unmasked, Face Recognition, Machine Learning, COVID-19 Pandemic

1.0 Introduction

A face recognition system is an intelligent system trained to detect and fish out a face in a pool of stored face images. Facial identification appears to be an old art that has existed for years and remained a research focus. Facial recognition began with considering face coordinates, followed by factors such as light illumination and skin condition, thereafter, using algorithms based on pattern matching approaches, posture, angle, distance and eigen values are determined (Turk and Pentland, 1991). Various face recognition methodologies, including the template approach, template and feature-based approaches, have been used to recognise faces (Kotropoulos *et al.*, 2000). The basic goal of machine learning-based image identification and classification is the extraction of image characteristics points and correct classification of picture attributes (Loussaief and Abdelkrim, 2018). Various machine learning algorithms such as, neural networks, support vector machines (Vapnik, 1995) , hierarchical knowledge-based method (Yang and Huang, 1994), Eigen face calculation, Euclidian heuristic, colour fractionalization, pattern appreciation, and sample matching have been used as test approaches. For security concerns, face identification methods are employed to authenticate faces in order to distinguish individuals. Facial recognition is implemented in both software and hardware template. The software implementation of facial identification is performed using template matching while the hardware execution takes place through implanted cameras incorporated with a program (Andrejevic and Selwyn, 2020).

Public and private companies exploit facial recognition systems in order to identify and monitor the access of people into their facilities (Talahua *et al.*, 2021). Other applications of face recognition systems include; surveillance systems, photo album organization, deployments of the face recognition systems for access control at airport borders (Carlos-Roca *et al.,* 2018), identity verification in financial services etc (Szczuko, *et al.*, 2019). The mandatory wearing of face shield in general environment coupled with other biosafety regulations to curb infections has created a need for improvement in face recognition systems (Talahua *et al.*, 2021).
The situation introduced a level of occlusion to face while the system's capability for recognition diminishes greatly (Talahua, *et al*, 2021). Thus, the choice of appropriate algorithm for accurate face recognition system cannot be over emphasised. This study, therefore, assessed the performance of some selected machine learning algorithms: Convolutional Neural Network (CNN), Linear discriminant analysis (LDA), Logistic Regression (LR), Naïve Bayes, K-Nearest Neighbour (KNN), Decision Tree (DT), Naïve Bayes (NB) and Support Vector Machine (SVM); and developed a face recognition system using the algorithm with the best performance.

Human faces were identified using only complexion fragmentation in YCbCrcolour expanse in (Kovac *et al.*, 2013), and the complexion colour states were as well produced in RGB colour expanse. A different technique for complexion colour modelling was done by utilising, Self-Organizing Map (SOM). Neural Network (NN), complexion segmentation was connected, and each segment was taken as a feature which was validated to know whether it could fit into an elliptic region or not (Chen *et al.*, 2009). Jee *et al.* (2006) applied complexion-like region segmentation based on YCbCr, to locate eye candidates with edge details in the region. The eyes were verified using SVM, look attributes were isolated with respect to eye position after validation and channelled to SVM for final categorisation. Another method is by adopting class-based SVM where face class was created instead of producing two classes; the face and the non-face, because of the complexity of modelling the non-face images. A real-time face recognition device that is precise, stable, and quick was proposed in (Kadry and Smaili, 2007), but requires improvement in various lighting conditions. Template matching was applied to spot look candidates in (Wang and Yang, 2008). The feature vector was extracted using Two-Dimensional Principal Component Analysis (2DPCA). The look matrix was straightly used on the 2D PCA instead of vector, and it minimised the operational time of calculating the covariance matrix. Initially, PCA must be applied, and minimum distance classifier was employed to categorise the PCA data for face and non-face cases. PCA was connected to the image to extract the face features at the beginning, while the feature images were categorised with Neural Network (NN), to eliminate non-face images. The final face candidates were verified with a geometry distribution of edges in the face region. Ruan and Yin (2009) divided complexion regions in YCbCrcolour expanse and looks were validated with linear support vector machine (SVM). Eyes and mouth were spotted with the information of Cb and Cr differences for final validation of face. For the eye region, the Cb estimate is higher than the Cr estimate, while for the mouth region, the Cr was higher than the Cb estimate. Another application divides the skin-like regions with a statistical model. The statistical model is made from skin complexion values in Cb and Cr channels in YCbCrcolour space. The face candidates were picked with respect to the rectangular ratio of the segmented region and the candidates were verified with an eye and mouth map.

Chen *et al.* (2009) used a mid-face template instead of a whole-face template to minimise mathematical time, it could also be used for face orientations. A different technique used imaginary templates that are not object-like but consist of some variables (i.e., size, shape, colour, and posture). Complexion-like regions is categorised with respect to YCbCr colour expanse. The segmented region is connected to the eye which paired the abstract templates. The initial templates spot the region of the eyes, while the next templates pinpoint the searched eye and determined its position. The touch template was connected to validate the look candidate region (Guo and Wang, 2019). The image-Based approach adopts training and learning methods for comparison between face and non-face images. An appreciable number of face and non-face images should be learnt on this method for an enhanced correctness of the software.

Lee and Liang (2010) spotted eyes and lips utilising the AdaBoost method. A feature vector was created based on eye, lip and nose region pixel values and distance between facial features. PCA and LDA reduce the feature vector dimension. The classification was done with RBNN. Embedded Hidden Markov Model (HMM) software was used for spotting and categorisation of looks. A separate program used RGB to partition skin-like regions, and the separated parts are subsequently validated using template matching. Detected faces are PCA extracted features of detected faces, and classification is done with similarity measures (Xuan and Nitsuwat, 2007). Segments of skin-like regions and look candidates were found with face symmetry verification. The rotation of the face is indicated by the eye template. The Haar wavelet attribute, gradient-based directional attribute, and gradient-based directional attribute were used to produce the attribute vectors, while the categorisation of the feature vector was achieved with NN (Xuan and Nitsuwat, 2007). (Hussain *et al*., 2012) proposed a face recognition system using Local Quantized Patterns and Gabor. They experimented with FERET and LFW datasets, the result obtained was robust to illumination variation;99.2% and 75% respectively. However, there were lot of discriminative information. Biswas *et al.* (2013), proposed using multi-dimensional scaling to convert features from low-quality probe images and high-quality gallery images at the same time. Roy and Bandyopadhyay (2013) introduced a hybrid method combining HSV and RGB for face recognition. The colour-based segmentation technique was used to detect and localise face area on single and multiple face images. Taleb *et al*. (2015) proposed an access control using automated face recognition. CA and LDA algorithms were used for face recognition with Viola – Jones for detection. Recognition of a driver's face seeking access to a park at *accuracy* of 92.88% with frontal pose was achieved. Accuracy varies with pose.

Abdolhossein *et al.* (2016) introduced the GaborZernike face feature descriptor and histogram of oriented gradients (HOG) descriptor to draw out local statistical features. The results were tested on ORL, Yale and AR databases, and accuracies of 98%, 97.8% and 97.1% respectively were obtained. In Wen *et al*. (2018), an improved look recognition with domain adaptation was proposed, and labelled faces in wild dataset was used as a benchmark to evaluate look recognition. Facenet triplet loss function was used and 99.33% accuracy was obtained with a single CNN model, without face alignment. The iris was another biometric that could be used in attendance software. Iris detection scheme based on the Daugmans algorithm was proposed by (Lin and Li, 2019). An iris recognition management system was used in this system to record, collect, store, and match iris recognition images. A multilevel authentication security scheme for controlling access to private and sensitive information against unauthorised users composed of face recognition at the first level and username/password authentication, at the other level was presented in (Odim *et al.*, 2019). Principal component analysis was used to model the face recognition and VB.Net password tool was used for the username and password. The scheme captured the faces of one hundred enrolled users with a webcam which were later used to assess the performance of the system. Results obtained showed that access could only be granted with the success of the joint authentication levels validation. It was however observed that wrong positioning of capturing devices could impede the accuracy of the scheme.

A face identification using KNN with Principal Component Analysis (PCA) was developed by Wirdiani *et al*. (2019). Pre-processing used in the work were contrast stretching, grayscale, and segmentation used haar cascade. Thirty people were registered for the experiment, 3 and 2 images of each person were used for training and testing respectively. The findings base a number of trials of k values revealed that, accuracies obtained as the value of k varies are 81% for k=1,53% for k=2, and 45% for k=3. Also, Tabassum *et al*. (2022) reported a human appearance classification with a combination of DWT and machine learning was presented. Discrete wavelet transform (DWT) was combined error vector of PCA, eigenvector of PCA, eigenvector of LDA and Convolutional Neural Network (CNN). Combination of the four results was achieved by using the entropy of detection probability and Fuzzy systems. The combined method provided a categorisation correctness of 89.56% for the worst case and 93.34% for the best case. However, the effect of illumination on recognition of the human face was ignored. Face recognition using deep learning, Convolutional (CNN) was presented in (Michael, 2010). The result achieved a 97% accuracy using CNN based on a pre-trained VGG Face for face recognition from a set of faces tracked in video or image capture. A comparative analysis of face recognition models on Masked Faces was presented in Chandra and Reddy (2020), VGG Face, Face Net, Open Face, Deep Face were used. VGG Face showed a superior performance 68.17% accuracy, 60.71% precision and 0.32s verification time. None of the pre-trained models with default weights performed well enough on masked faces (Chandra & Reddy, 2020).

Convolutional Neural Network (CNN) was combined with augmented dataset in (Lu, Song, & Xu, 2021) to tackle the problem of human face recognition on small original dataset. The dataset though small was augmented to increase the size of the dataset through several transformation of the face images. The feature of the augmented faces was extracted successfully, thus increasing face recognition accuracy obtained using CNN. The performance of CNN was evaluated through a number of experiments and it offered superior performance when compared with some commonly used face recognition techniques. The approach recorded an accuracy of 99.5% against ANN with 80.3%, PCA+ANN with 91.0%, PCA+SVM with 97.4%, Wavelet+SVM with 98.1% and Wavelet+PCA+SVM with 98.0% accuracy respectively. However, the study did not consider data face with masked faces. Thus, one cannot ascertain the capability of the system for recognition of masked faces. Talahua *et. al* (2021) presented facial recognition system for People with and without facemask fo-r the COVID-19 Pandemic. MobileNet, Vface detector and facenet were used for feature extraction. The system was able to detect persons with or without mask with 99.65% accuracy. The system could only detect face. This study assessed the performance of seven machine learning algorithms and developed a face recognition system for access control.

2.0 Methodology

The performance of seven machine learning algorithms: Convolutional Neural Network (CNN), Linear discriminant analysis (LDA), Logistic Regression (LR), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Naïve Bayes (NB) and Decision Tree (DT) were assessed using online repository datasets downloaded from the Kaggle website; composed of masked and unmasked face images (https://www.kaggle.com/jessicali9530). After loading the dataset to the computer's local drive, it was imported to a Jupyter notebook, where preprocessing was done, features were selected, and the data was split into 70% training and 30%

testing sets. The seven models (CNN, LDA, LR, KNN, SVM, NB, DT) were applied individually to the training sample and testing done on all the models as depicted in figure 1. The performances of the models were evaluated and the algorithm with the superior performance in terms of accurate face recognition capability was adopted and used to develop a face recognition system for access control.

2.1 Data Description

The dataset was composed of masked and unmasked face images (https://www.kaggle.com/jessicali9530) organised into three folders viz; train, test, and validate with subfolders for each image category marked as 'With Mask and Without Mask'. The data contains a total of 11972 face images consisting of 5883 images with facemasks and 5909 images without facemasks. The Kaggle images with the face mask were scratched from google search, while the images without the facemask were pre-treated from the CelebFace (https://www.kaggle.com/jessicali9530). Images were of 60x51 in size and converted to Gray Scale colour space.

2.2 Data pre-processing

The Principal Component Analysis (PCA) was used for feature dimensionality of the images. PCA is a dimensionality decimating method where huge data sets are scaled down and many variables are converted to smaller sets that preserve the majority of the key element. Naturally, a data set's precision suffers when the number of variables is reduced. However, substituting some accuracy for simplicity is the key to dimensionality reduction. Machine learning algorithms examine data effectively without dealing with superfluous variables. Moderate data sets are easier to test and predict. (Zheng, 2021). The data were converted into new components using this method, and the size of the data was reduced by choosing the most essential components. The process starts by determining the direction of the maximum variation, this is the direction in which the majority of the data was associated, or in other words, the attributes that were most closely related to one another. When the algorithm is orthogonal (at a right angle), it determines which direction in the first direction contains the greatest information. In two dimensions, there is only one potential

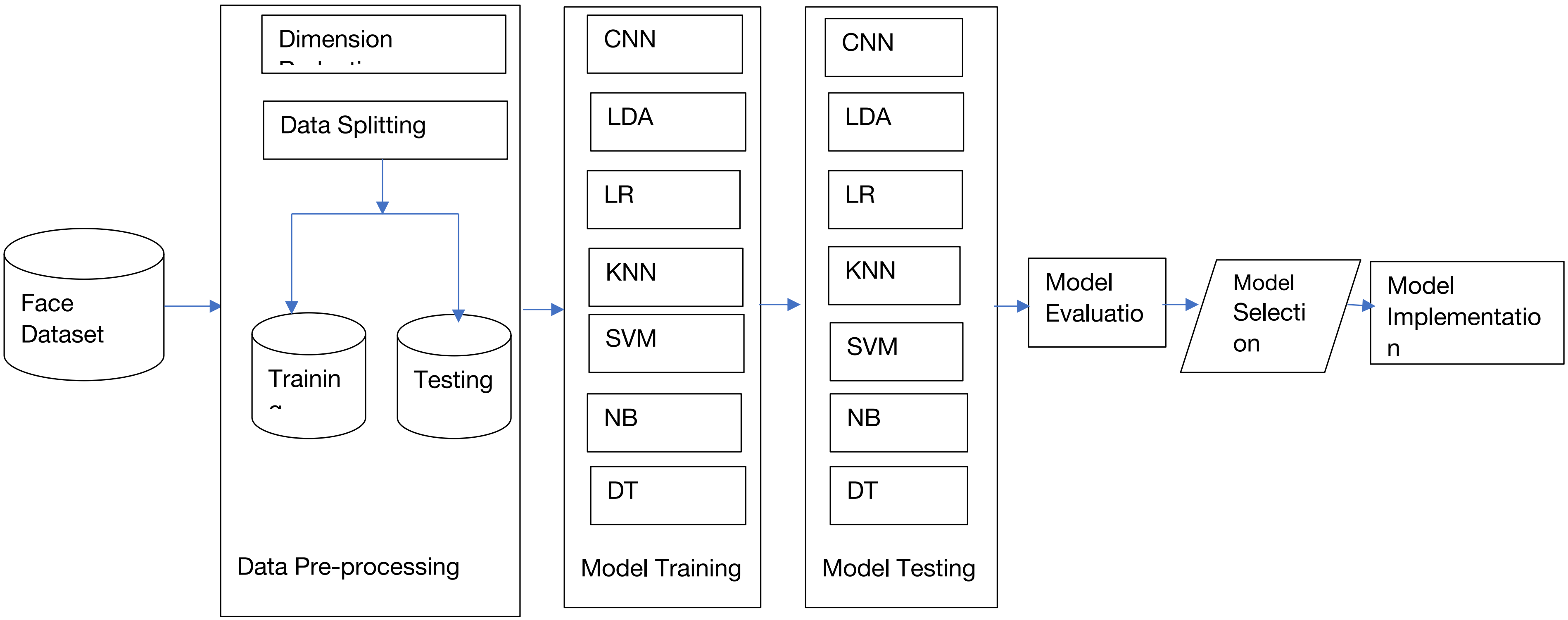


Figure 1: System Architecture of Face recognition system orientation at a right angle, but in high-dimensional spaces, there will be numerous orthogonal directions (infinite). To reduce noise from the dataset, each pixel was examined relative to its neighbour with a window size of 5 x 5. An averaging operator and a gradient operator are comparable (for noise removal). Each sub-median window's value was calculated, and the median values of three consecutive windows were sorted in ascending other. The median values from the three consecutive windows were then used to replace the centre pixel and its neighbours inside each window. To maintain the image's sharpness, this technique was repeated for all pixels. To reduce the number of grey tones in the input photos, the watershed method was used. To reduce the impact of brightness disparities, a grayscale normalization was used. To prevent overfitting, rotation of data augmentation technique was used. Some training images were randomly rotated by 30°, randomly magnified by 20%, randomly shifted images horizontally by 10% of the width, vertically by 10% of the height, and horizontally flipped images. After preprocessing, the data were divided into Training, testing, and validating at the ratio 70%,20% and 10% respectively, as shown in Figure 1.

2.3 The Selected machine learning Algorithms

Seven machine algorithms were assessed for the development of the face recognition system. The algorithms were Convolutional Neural Network (CNN), Linear discriminant analysis (LDA), Logistic Regression (LR), K-Nearest Neighbour (KNN), and Support Vector Machine (SVM). These algorithms have been used over time for face recognition systems, KNN with PCA (Wirdiani, *et al*., 2019); CNN Michael, (2010); (Lu, Song, & Xu, 2021); DWT with PCA (Tabassum, Islam, Khan, & Amin, 2022); CA and LDA (Taleb *et.al*., 2015); KNN (Eko & Adharul, 2015)

2.3.1 The Convolutional Neural Network

Convolutional neural network (CNN) is a neural network with convolutional layers. Principally, CNN consists of convolutional layers and pooling layers in its hidden layers, these could be arranged in any order in the neural network. The connection weights of CNN can be shared in the whole neural network, this would reduce the amount of the connection weights, as well as simplify the complexity of the network model, thus, reducing the training time of CNN. Owing to the advantages of weight sharing, pooling and local receptive field, CNN has a robust performance on several image transformation operations, e.g. translation, rotation, and scaling (Lu, Song, & Xu,

2021) . Figure 2 depicts a CNN showing the various layers, convolution, pooling and fully connected layers.

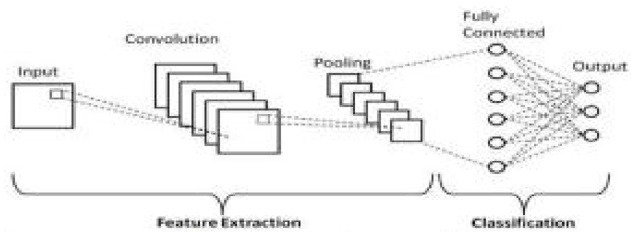


Figure 2: Convolutional Neural Network (Van and Eun, 2019).

The CNN model for the face recognition

The structure of the CNN model for the face recognition for both masked and unmasked faces, is shown in Figure 3 The convolution operation is a fundamental construction block of convolutional neural network. The parameters of the convolutional layers involve a set of learnable filters (kernels). Filters are spatially small (along the width and the height), they extend through the full depth of the input volume. Typical filter shapes might have sizes 3x3, 5x5, 7x7. During forward propagation, convolution is conducted on input volume across the height and width by every filter and dot product are computed across filter's entries while nonlinear activation function follows input at any position. The resulting products are called feature maps or activation map. This feature map gives the response of the filter at every spatial position.

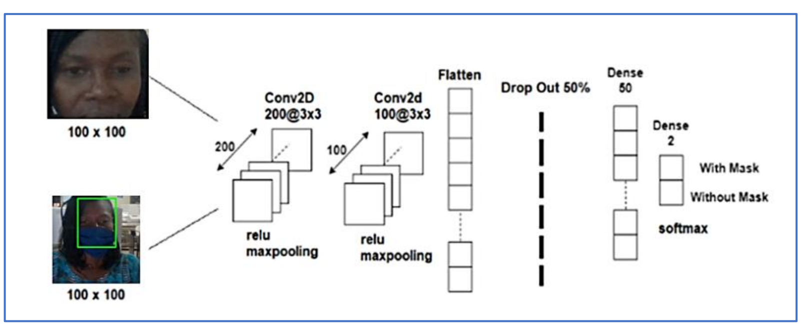


Figure 3: The CNN model for the masked and unmasked face recognition

The input to the model consists of masked and unmasked face images. The model consists of two convolution layers, each followed by a Rectified Linear Unit (relu) activation function and a max-pooling layer. The relu function was introduced to cater for non-linearity in CNN. The max Pooling was used for the reduction processing of the image, there are no parameters for the pooling layer to learn. The Max pooling takes the largest elements from the rectified feature map, flattens the data by converting it to 1- dimensional array as input to the final output layer. A fully connected single-layer perceptron is located between the second relu maxpooling layer and the output layer (with two output alternate mapping: masked or unmasked face).

2.3.2 Linear discriminant analysis (LDA)

Fisher's linear discriminant is a method for determining a linear combination of characteristics that differentiates two or more classes of objects or events that are used in statistics and other areas. An extension of Fisher's linear discriminant analysis includes linear discriminant analysis (LDA), normal discriminant analysis (NDA), or discriminant function analysis. The subsequent combination can be used as a linear classifier or, more typically, for dimensionality reduction before further classification. LDA seeks for linear combinations of variables that best describe the data. LDA is an explicit attempt to model the differences across data classes.

2.3.3 Logistic Regression (LR)

Logistic regression is a supervised learning algorithm useful for categorisation. It uses a logistic function to model the dependent variable with only two states, which is either 0 or 1. A linear classifier is the most basic and commonly used machine learning model. A typical linear logistic equation is depicted in equation in.

$$Z = b_0 + b_1x_1 + b_2x_2 + \cdots\cdots + b_nx_n = \sum_{n=0}^{\infty} b_nx_n \quad (1)$$

where, z is the dependent variable, b is the regression beta coefficient and x_i are the explanatory or independent variable.

z can only be between 0 and1, hence dividing the above equation by 1-z, we get;

$$\frac{Z}{1-Z} = \sum_{\infty,\ z=1}^{0,\ z=0} \quad (2)$$

$$\text{Therefore, } \frac{Z}{1-Z} = \frac{\sum_{n=0}^{\infty} b_nx_n}{1- \sum_{n=0}^{\infty} b_nx_n} = \frac{b_0 + b_1x_1 + b_2x_2 + \cdots\cdots + b_nx_n}{1-(b_0 + b_1x_1 + b_2x_2 + \cdots\cdots + b_nx_n)} \quad (3)$$

Taking log of the above, we get

$$\text{Log}\ \frac{Z}{1-Z} = \log\left(\frac{\sum_{n=0}^{\infty} b_n x_n}{1-\sum_{n=0}^{\infty} b_n x_n}\right) \quad (4)$$

2.3.4 K-Nearest Neighbour (KNN)

One of the basic concepts of K-Nearest Neighbour includes having multiple training and testing samples determined by members. If k=1, the testing sample is assigned to the nearest single neighbour class. However, how to find the right k value for a particular case is a problem that affects the performance of the KNN (Eko and Adharul, 2015). The classification stages in face identification systems use the K-Nearest Neighbor (KNN) method where the eigen image of the feature extraction process used as input. The algorithm recognises faces based on classification of each pixel. The face was determined by highest classes obtained in each pixel classification. In recognition, the pixel matrix of the face image should be reshaped into a vector before classification.

2.3.5 Support Vector Machine (SVM)

Support vector machine (SVM) is a machine-learning approach based on the structural risk reduction principle. Based on the ability of SVM to find solutions to problems of scanty training samples, long dimensions, and nonlinearity, the technique has become renowned in the past decades as a modern machine-learning technique in many fields, like pattern recognition, and other nonlinear difficulties with small sample sizes. SVM has a firm theoretical base and a sound generalization capability. From the implementation point of view training an SVM classifier corresponds to solving a linearly constrained quadratic programming (QP) problem with high time and space complexities with increase in sample size.

2.3.6 Naïve Bayes

Naïve Bayes algorithm is a probabilistic classifier based on the Bayes Theorem that is efficient when input dimensionality is high. It assumes that every feature in a class is highly independent, implying that the appearance of a feature in a particular class is not related to any other feature. Naïve Bayes classifier is built on the motive that the role of a natural class is to estimate the values of features for members of that class (Oguntunde, Arekete, Odim, & Ariyo-Agbaje, 2020). For a given input window, a feature vector x is extracted, this feature vector can be classified either as face or nonface according to the Bayesian decision rule. Let $p\,(x|\gamma_{face})$, and

$p\ (x|\gamma_{nonface})$ be the class-conditional pdfs of face and nonface classes. The feature vector can be classified as a face pattern if the following log-likelihood score exceeds a threshold:

$$g(x) = \log(p\ (x|\gamma_{face})) - \log\ (p\ (x|\gamma_{maskedface})\ ) \quad (5)$$

Where x is a feature vector extracted from the image

In this study, the feature vector was classified into face masked, unmasked or nonface class with some modification of the Bayesian decision to accommodate the three classes, as follows: Let $p\ (x|\gamma_{umaskedface})$, and $p\ (x|\gamma_{maskedface})$ and $p\ (x|\gamma_{nonface})$ be the class-conditional pdfs of unmasked face, masked face and nonface classes, respectively. The feature vector was classified as an unmasked face pattern if the following log-likelihood score exceeds a threshold:

$$g(x) = \log(p\ (x|\gamma_{unmaskedface})) - (\log(p\ (\ x|\gamma_{nonface}))\ U\ \log\ (p\ (x|\gamma_{maskedface})\ )) \quad (6)$$

The feature vector was classified as a masked face pattern if the following log-likelihood score exceeds a threshold:

$$g(x) = \log(p\ (x|\gamma_{maskedface})) - (\log(p\ (\ x|\gamma_{nonface}))\ U\ \log\ (p\ (x|\gamma_{unmaskedface})\ )) \quad (7)$$

The class condition PDF was estimated by the naïve Bayes model as in _(Phung, Bouzerdoum, Douglas, & Watson, 2004) _. The naïve Bayes model assumes statistical independence among elements of the feature vector **x**. Under this assumption, we obtain:

$$p\ (x|\gamma_{umaskedface}) = \prod_{i=1}^{N} p\ (x_i|\gamma_{unmaskedface}) \quad (8)$$

$$p\ (x|\gamma_{maskedface}) = \prod_{i=1}^{N} p\ (x_i|\gamma_{maskedface}) \quad (9)$$

$$p\ (x|\gamma_{nonface}) = \prod_{i=1}^{N} p\ (x_i|\gamma_{nonface}) \quad (10)$$

The marginal pdfs $(x_i|\gamma_{unmaskedface})$, $p\,(x_i|\gamma_{maskedface})$, and $p\,(x_i|\gamma_{nonface})$ were calculated using the histogram technique, also as in In (Phung, Bouzerdoum, Douglas, & Watson, 2004).

2.3.7 Decision Tree

Decision tree is a tree-like structure, built by breaking a dataset down into smaller subsets while an associated decision tree is incrementally developed concurrently. The outcome is a tree with decision and leaf nodes. A decision node can have two or more branches, while the leaf node represents the decision or classification. For face recognition, local binary patterns (LBP) were introduced as a fine scale texture descriptor (Mikolajczyk and Schmid, 2005). In its simplest form, an LBP description of a pixel is created by thresholding the values of a 3 × 3 neighbourhood with respect to its central pixel and interpreting the result as a binary number. In (Maturana *et al.*, 2010), an LBP operator assigns a decimal number to a pair (c, n),

$$b = \sum_{k=1}^{s} 2^{i-1} I\,(c, n_i) \tag{11}$$

where c represents a centre pixels, n = (n_1,…, n_S) corresponds to a set of pixels sampled from the neighbourhood of c according to a given pattern, and I(c, ni) = 1 if c

where c represents a center pixel, n = (n_1,…,n_S) corresponds to a set of pixels sampled from the neighborhood of c according to a given pattern, and

$$I\,(c, n_i) = \begin{cases} 1 if\ c > n_i \\ 0 otherwise \end{cases} \tag{12}$$

This can be seen as assigning a 0 to each neighbor pixel in *n* that is larger than the center pixel *c*, a 1 to each neighbor smaller than *c*, and interpreting the result as a number in base 2. In this way, for the case of a neighborhood of S pixels, there are 2^S possible LBP values.

2.4 Evaluation Metrics

The evaluation of the face recognition capability of the algorithms was carried out using the confusion matrix using the following metrics, accuracy, Precision, Sensitivity and F1 score. The accuracies of the models were then compared. Equation (13) presents the expression of accuracy as defined by the confusion matrix.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

where TP (True Positive) represents the positive instances correctly classified as positive (authorized faces correctly identified), TN (True Negative) is the negative instances classified as negative (Unauthorized faces identified as unauthorized), FP (false Positive) denotes the negative instances incorrectly classified as positive (unauthorized faces wrongly identified as authorized) and FN (False Negative) refers to the positive instances that were erroneously classified as negative (authorized faces wrongly identified as unauthorized).

3.0 Result and Discussion

This section presents the result and discussion of some experimental analysis conducted to access the performance of the various algorithms considered. The algorithms were implemented in Python, using relevant libraries.

3.1 Comparison of the algorithms' Recognition Accuracies

Figure 4 shows the screenshot of the code segments of the training of the face recognition using CNN.

```
In [51]: epochs = 20
         INIT_learning_rate = 0.0001
         opt = Adam(lr=INIT_learning_rate, decay=INIT_learning_rate / epochs)

In [52]: # BUILD CNN
         nets = 5
         model = [0] *nets
         for j in range(nets):
             model[j] = Sequential()
             model[j].add(BatchNormalization(input_shape=input_shape))
             model[j].add(Conv2D(32, (3, 3), padding='valid'))
             #model[j].add(BatchNormalization())
             model[j].add(Activation('relu'))
             #model[j].add(Dropout(0.4))
             model[j].add(MaxPooling2D(pool_size=(2, 2)))
             model[j].add(Dropout(0.5))

             model[j].add(Conv2D(32, (5, 5), padding='same'))
             #model[j].add(BatchNormalization())
             model[j].add(Activation('relu'))
             model[j].add(MaxPooling2D(pool_size=(2, 2)))

             model[j].add(Conv2D(64, (5, 5), padding='same'))
             #model[j].add(BatchNormalization())
             model[j].add(Activation('relu'))
             model[j].add(MaxPooling2D(pool_size=(2, 2)))

             model[j].add(Conv2D(128, (5, 5), padding='same'))
             #model[j].add(BatchNormalization())
             model[j].add(Activation('relu'))
             model[j].add(MaxPooling2D(pool_size=(2, 2)))

             model[j].add(Flatten())
             #model[j].add(Dense(128))
             #model[j].add(Activation('relu'))
             model[j].add(Dense(256))
             model[j].add(Activation('relu'))
             model[j].add(Dropout(0.5))
             #model[j].add(Dense(32))
             #model[j].add(Activation('relu'))

             model[j].add(Dense(2))
             model[j].add(Activation('softmax'))
             model[j].summary()
```

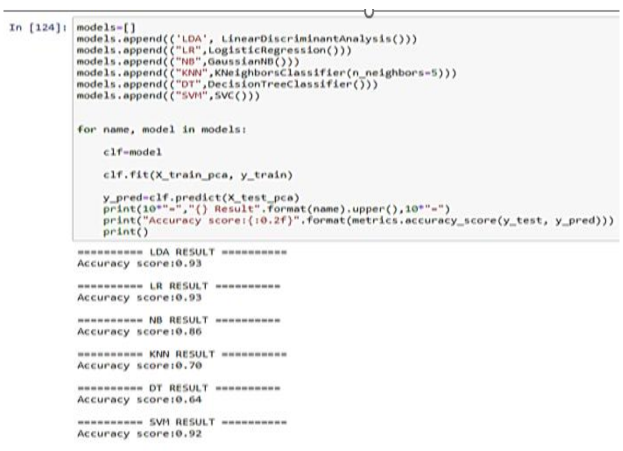
	precision	recall	f1-score	support
0	0.99	0.99	0.99	508
1	0.99	0.99	0.99	484
accuracy			0.99	992
macro avg	0.99	0.99	0.99	992
weighted avg	0.99	0.99	0.99	992

(a)Training (b) Performance results

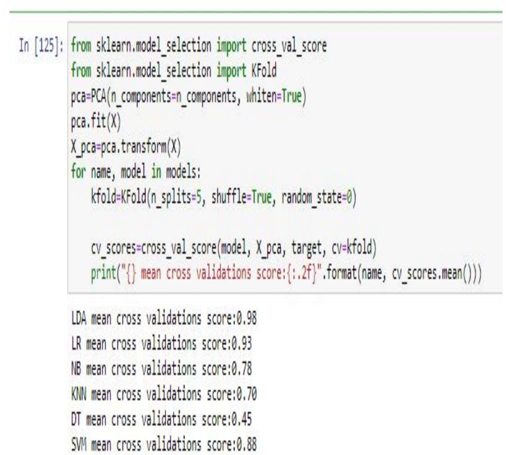
Figure 4: Code segment and performance output of the CNN

The learning rate was initialised to 0.00001 with 20 epochs. The accuracy and other evaluation metrics obtained from the training are depicted in the screenshot in Figure .

The screenshot for the face recognition training and cross validation with LDA, LR, NB, KNN, DT and SVM is depicted in Figure 5. The analysis recorded accuracy of 93%, 93%, 86%, 70%, 64% and 92% respectively for the LDA, LR, NB, KNN, DT and SVM.



(a) Code segment of the training



(b) code segment of the cross validation

Figure 5: code segment and accuracy output of LDA, LR, NB, KNN, DT and SVM

Training and cross validation accuracies of the algorithms are summarised in Table 1 and Figure 6 presents same information graphically.

Table 1. Summary of the training and cross validation accuracies

Algorithm	Accuracy	
	Training	Cross - Validation
CNN	99%	99%
LDA	93%	98%
LR	93%	93%
NB	86%	78%
KNN	70%	70%
DT	64%	45%
SVM	92%	88%

CNN recorded the highest accuracy for both the training cross validation of 0.99 each. Therefore, CNN was chosen for the development of

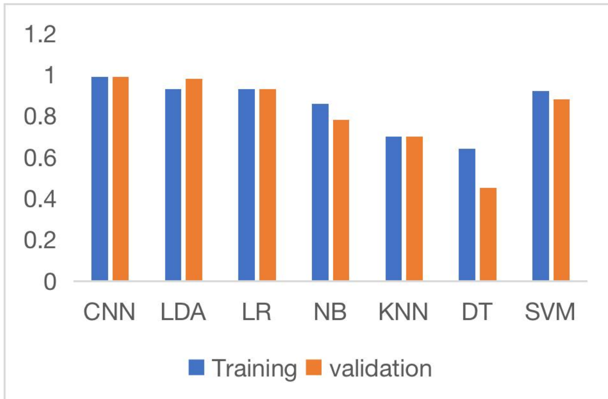
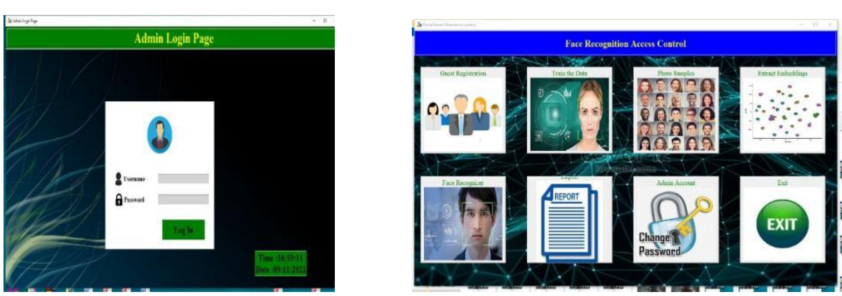


Figure 6: Performance accuracy of the algorithms

3.2 The Face Recognition System for Access Control using CNN

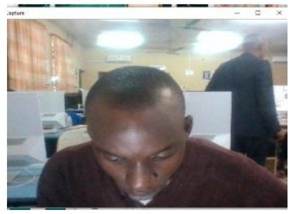
The system was developed to serve as a face recognition application for access control. It involved three phases, viz; registration phase, training phase and testing phase as discussed earlier. Figure 7(a) shows the log in interface of the system, while Figure 7 (b) system actives interface. The registration phase with the gust's credentials, including the face capturing is depicted in Figure 8.



(a) Login (b) System activity interface

Figure 7: Login interface and the system activities of the face recognition access control system

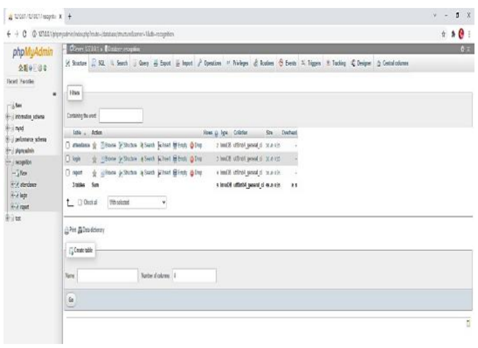
(a) Registration Interface view



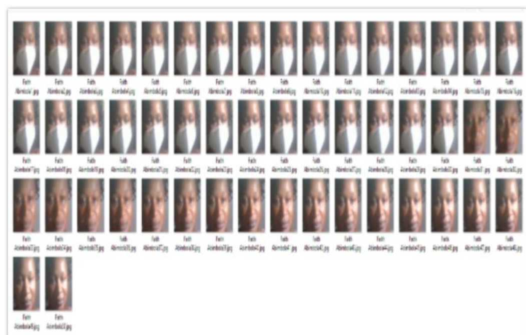
(b) Camera view of the system

Figure 8: Registration Interface and camera view of the system

The database that stores the identity of registered guest is shown in Figure 9 (a), while the Figure 9 (b) show a sample of training images for masked and unmasked faces.



(a) System Database

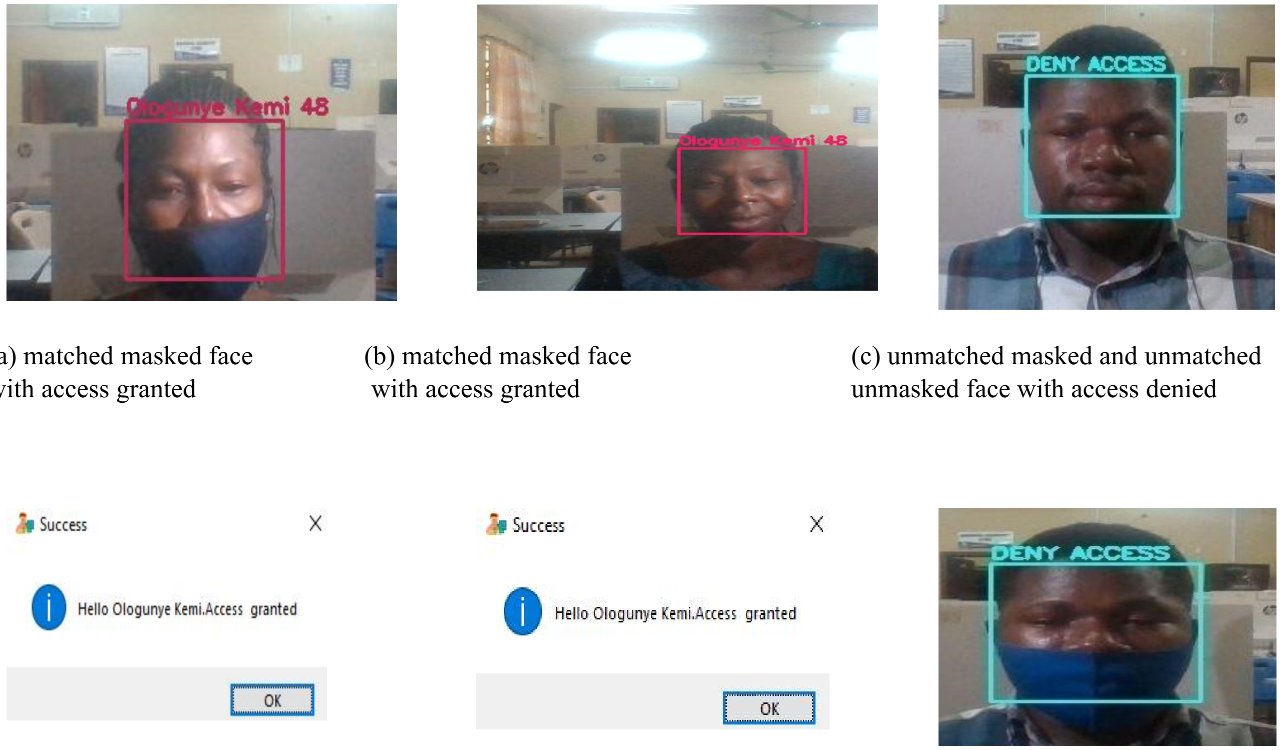


(b) Trained face images (masked and unmasked)

Figure 9: Database for face recognition-based access control

A total number of sixty-seven people were used for testing. Forty-seven of them were registered, and stored in the database, while twenty were not registered. The system, while testing, showed the 47 registered people accurately with each one of them granted access while the 20 unregistered people were correctly denied access. The training phase involved extraction of the embedded face.

The test phase involved authenticating the face and granting access. The face image of the Guest is detected, captured and compared with the images in the database for a match. A recognized face is acknowledged by the system with a name, and access is granted, while a face that is not matched in the database is denied access. Figures 10 showed the results of testing for registered Guest (both masked and unmasked) and unregistered face images (masked and unmasked).



(a) matched masked face with access granted

(b) matched masked face with access granted

(c) unmatched masked and unmatched unmasked face with access denied

Figure 10: The testing phase of the system.

3.3 Comparison of Results

Results from related studies were compared with the obtained result in this study, as shown in Table 2. The comparison with related study showed that the proposed model competes favourably with the existing ones, with its CNN and LDA standing tall. The CNN with accuracy of 99%, LDA with 98% and LR with 93% accuracies from the proposed models demonstrated the superiority of the proposed models to the existing one.

Table 2: Comparison of results with related studies

Authors	Classifier used	Dataset	Accuracy%
Zia et.al 2018	Deep Belief Network (DBN), OpenCV	Kaggle	79% 76%
Michael. (2020)	(CNN), (LDA), PCA	Yale	ACCURACY-95%
Yalavarthi and Gouru. (2020)	VGG Face, Face Net, Open Face, Deep Face.	Kaggle	VGG Face=68.17% Face net=59.48% Deep face=55.42% Open face=52.55%
Proposed (2022)	CNN, LDA, LR, KNN, SVM, Naïve Bayes and Decision Tree	Kaggle	CNN = 99% LDA= 98% LR = 93 % KNN = 70% SVM = 88% NB = 86% DT = 64%

4.0 Conclusion

This study presents a robust face recognition system that is capable of recognising faces with or without face covering (masks) to a high degree of accuracy. The performances of the following selected machine learning algorithms were compared: Convolutional Neural Network (CNN), Linear discriminant analysis (LDA), Logistic Regression (LR), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Naïve Bayes (NB) and Decision Tree (DT) for recognition of masked and unmasked human faces; and developed a face recognition system adopting the best outperformed algorithm, using face images from Kaggle repository. The findings revealed that CNN recorded the highest recognition accuracy with 99% for both the training and validation sets. Thus, a CNN user-friendly face recognition, system was developed and tested with a number of real-life human masked and unmasked faces which showed excellent recognition performance. The developed system could be very useful for access control and surveillance. Therefore, this study recommends the adoption of the developed systems for face recognition-based security system.

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