# Implementation of an Embedded Masked Face Recognition System using Huskylens System-On-Chip Module

Okokpujie Kennedy
*Department of Electrical and Information Engineering, Covenant University, Ota, Ogun State, Nigeria*
*https://orcid.org/0000-0002-7594-276X*

Anicho-Okoro Chiamaka
*Department of Electrical and Information Engineering, Covenant University, Ota, Ogun State, Nigeria*
*https://orcid.org/0000-0002-7594-276X*
*amaka.anicho@gmail.com*

*Okokpujie Imhade Princess*
*Department of Mechanical and Mechatronics Engineering, Afe Babalola University, Ado Ekiti, Nigeria*
*Department of Mechanical and Industrial Engineering Technology, University of Johannesburg, 2028, South Africa, https://orcid.org/0000-0001-6600-6710*

*Okesola Julius-Olatunji*
*Department of Computational Sciences First Technical University, Ibadan, Nigeria*
*olatunjiokesola@tech.U.edu.ng*

***Abstract*—Globally, Facial recognition systems have been increasingly adopted, by governments, as a viable means of identification and verification in public spaces such as the airport, train stations, and stadiums. However, in the wake of the COVID-19 outbreak, the World Health Organization (WHO) declared that wearing face masks is an essential safety precaution. As a result, current facial recognition systems have difficulties recognizing faces accurately, which motivated this study. This research aims to implement an embedded masked face recognition system using the HuskyLens SoC module to identify people, even while wearing a face mask. The developed method was actualized using the Kendryte K210 chip embedded in the HuskyLens module. This system-on-chip design was integrated with other peripherals using an Arduino Pro-mini board. The results of testing and evaluating the system's performance show that the system's facial recognition accuracy with masked and without masks faces was 90% and 95%, respectively. Implementing this solution in our environment would enable accurate real-time recognition of masked and unmasked faces**

***Keywords—facial recognition, COVID-19, HuskyLens, Kendryte, masked faces***

## I. Introduction

Over the years, there has been a rapid enhancement in human-computer interaction and face recognition studies. These were based on the discovery that the human face contains certain information, including one's identity, age group, race, sex, and facial gestures, that reflect a person's emotional and mental state [1]. A computer can extract and interpret this information to either identify or verify that person's identity [2][17]. For these reasons, the human face has become one of the most widely used and preferred biometric authentication methods.

Globally, Facial recognition systems have been increasingly adopted by governments as a viable means of identity verification in public spaces such as the airport, train stations, stadiums, etc. It does not require the involvement of personnel to operate. Just the presence of an individual in front of the camera is enough [3][18]. Some other features which have made face recognition systems more attractive include: The ability to capture faces and process them in real-time; Its ability to work with both images and videos in the capturing process; The system is independent of the person (meaning irrespective of race, gender, and ethnicity).

Security agencies worldwide are also implementing face recognition technology to eradicate terrorists and drug traffickers across borders [4]. Other activities such as access control in commercial buildings and identity verification, in general, are also increasingly dependent on face recognition technology. However, given the current pandemic situation, the use of face masks has been enforced in many countries in public spaces to prevent further transmission and curb the widespread of the COVID-19 virus [5][20]. The virus is spread through direct contact with the respiratory droplets of an infected person. Hence, other biometric procedures that involve the use of fixed physical traits such as fingertips, handprints, and the like are not recommended since the virus can easily be transmitted through touch [6][19]. Before this, numerous establishments that had been using a fingerprint or card-based biometric system had to switch to a face-based biometric system to avoid direct contact with the system [4][21].

Due to the advent of COVID-19 and the enabling law across the world's various countries to cub the transmission, it is now illegal to take off one's face mask in a public setting, even for identification. As a result, there is a growing need to improve the accuracy of current face identification technologies on faces covered with masks. [7]

This research aims to develop and implement a masked face recognition system that can accurately recognize and identify individuals while they are wearing face masks using the HuskyLens SoC module.

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## II. RELATED WORKS

### *A. Summary of Efforts*

First, the work [8] discussed this global COVID-19 outbreak and how putting on a mask protects people from contracting the virus. However, this poses significant hurdles to the current facial recognition technology. Therefore, described a new technique for recognizing masked faces in this paper. This approach combines a method centered on cropping out the masked portion of the face with the Convolutional Block Attention Module (CBAM) to overcome these challenges. There are two unique application scenarios: utilizing unmasked faces to train the model to recognize masked faces and vice versa. The two use scenarios were well investigated using the CBAM module, which focused solely on the eyes' area. Also, optimal cropping was examined for each example. Extensive tests on multiple masked face datasets reveal that their proposed method outperforms previous algorithms in recognizing masked faces using intrinsic facial features such as the ocular and periocular portions of the face, thus requiring user cooperation. Therefore, the suggested model is not helpful in uncontrolled or uncooperative circumstances, such as video surveillance in public settings.

Efforts in [9] demonstrated a technique for learning masked faces by detecting and removing corrupted face characteristics from identification, considering that human vision overlooks obstruction and focuses entirely on visible face components. Using an innovatively built "Pairwise Differential Siamese Network (PDSN)", a dictionary for masks is initially created utilizing the disparities amongst obstructed as well as visible facial features on both faces. The Feature Discarding Mask (FDM) feature of the dictionary describes the relationship between obstructed parts of the face and the corrupted face features. The Feature Discarding Mask is constructed by combining appropriate dictionary elements and multiplying them with the original features to eliminate the damaged features. This was done with a face image with partial occlusions. Extensive research on the synthetic occluded face datasets and the real-life datasets of occluded faces demonstrates that the proposed technique outdoes existing methods. However, Deep-CNN models, on the other hand, cannot work properly unless they are trained explicitly with a significant number of images of occluded faces. Properly training the network with genuinely obstructed face images is one potential way to improve CNN models' behavior under partial occlusions.

The authors [10] offer to Face Attention Network (FAN). This unique face detector can considerably improve the face identification problem in an occluded scenario without affecting computational speed. Features from visible regions of the face were highlighted, thus successfully reducing the risk of false positives. However, features may be harder to extract with this approach. The work [11] used a deep learning-based method to extract features from only the upper part of the face. The authors proposed a method to eliminate the problems of masked face recognition. This study deals with only the informative regions of the face, the revealed parts of the face, thus making it applicable in real-time, unlike other methods that deal with regeneration or image completion. Also, the smaller the processed region of the face is, the faster the trained model performs. However, there is information loss when dealing with unmasked faces, so this approach is unsuitable for applications that combine both use cases: both masked and non-masked faces. Nonetheless, this study is still useful in the future, even after the Pandemic, as people remain self-aware and still prefer to have a mask on for protection against viruses.

The work [12] describes the use of PCA for occluded and unmasked identification. There has been little advancement in recognizing masked faces as a research topic. To address this issue, PCA, a more efficient, robust, and extensively utilized statistical technique, has been chosen for this study. A test was performed on both masked and unmasked face images, and it was discovered that the recognition accuracy for masked face images was around 72%, while the accuracy for unmasked faces was around 95%. This experiment demonstrated that an unmasked face image has a higher identification level in a face recognition system centered on Principal Component Analysis. However, with masked faces, there are low recognition rates. This approach is not very efficient for masked face recognition.

The authors [13] studies compared the behavior of cutting-edge facial verification models on the recognition of masked face images. They compared four trained models: VGGFace, Facenet, OpenFace, and DeepFace. To verify faces, they used the RMFRD database. Note that, in one verification, VGGFace had the best accuracy (68.17), precision (60.17), and time (0.32s). On the LFW dataset, VGGFace has an accuracy of 99.13%, compared to 68.17% on the RMFRD dataset, indicating a huge variation in the percentage of accuracy. Thus, it is possible to deduce that the performance of these models suffers when dealing with masked face images. Methods such as transfer learning and fine-tuning can be used to improve the performance of these models.

The paper [14] proposed a way to enhance existing facial datasets with technologies that allow the identification of occluded faces with low levels of false positives and good accuracy so as not to rebuild the database by capturing fresh photographs to be used for verification. They demonstrate MaskTheFace, an open-source program for masking faces and producing a huge collection of masked faces. This yielded a dataset. The technology is employed to develop an accurate system for the recognition of masked faces. They reported a 38% rise in the Facenet system's true positive rate. They claimed that the Facenet system's true positive rate increased by 38%. They also tested the retrained system's accuracy on a real-world dataset created specifically for users called MFR2. This was found to be similar. However, the system exhibited a long training time of over 42 hours. Nonetheless, this tool would be useful in real-time situations for real-life masked faces.

The work [15] addressed the issue of face recognition using masks in this paper. A complete training pipeline based on the ArcFace work is presented to address this issue. A masked replica of the original face-recognition dataset is created. Both datasets are integrated throughout the training phase, and data augmentation is used. The proposed method highly enhances the accuracy of the original model when dealing with masked faces while also maintaining a similar accuracy on the original unmasked datasets. An average accuracy of 99.78% was achieved in the classification of mask usage. However, this approach exhibits a significant performance drop with unmasked faces. Prospective work should focus on extending the range of applicability of this method to other occlusion types, such as eye-masked faces.

The work [16] driven by recent advances in amodal perception suggested transferring the amodal completion mechanism usually used to recognize masked face images to a complete de-occlusion distillation system comprising of units, namely: de- occlusion and the distillation module. The module performs face completion for de-occlusion using a network that recovers the material under the mask and removes appearance uncertainty. The module for distillation uses a generic algorithm that has already been trained as the teacher, then uses huge online synthesized face pairs for student training. Experiments with simulated and real-world data demonstrate the usefulness of the suggested method. However, the remodeled faces are synthetic, and their reliability is dependent on the data quality, the network itself, and the entire training process. Also, the process of removing the mask increases the computation time.

In this digital age, this study is highly relevant. It helps to solve the partial occlusion caused by the face masks, preventing face recognition technologies from effective detection, and hindering real-time applications such as access control in industrial buildings and attendance taking in institutions, etc. Also, as there is currently no fully implemented technology for face recognition on masked faces, this study is entirely necessary.

The contribution of this paper is to harvest a dataset of masked and unmasked faces photographed in the real world and a prototype with high accuracy of masked face recognition. This research also addresses the flaws in existing face recognition systems by decreasing image enrolment and processing time and improving face recognition accuracy on masked faces.

## III. METHODOLOGY

The stages of the system operation follow the fundamental face recognition pipeline, which comprises two key phases: enrolment and recognition. These phases are represented in Fig. 1.

### *A. Enrollment Phase*

- Data Acquisition

The initial stage of a face recognition system is image capture. After that, several image processing procedures may be applied to the acquired images and then enrolled into the system database. A collection of self-captured pictures was used in this study.

- Image Capture

The images required for this project were captured using an 8Mp iSight camera which records at 1080p resolution.

A total of 200 images of 100 subjects were captured in multiple sessions, with two pictures each. The subjects directly face the camera in a controlled scenario. These are the scenarios:

- the mask covering the nose and mouth
- no mask

The target group captured was final year students of Covenant University between the ages of 18-and 24. The dataset is made up of 200 subjects-male and females. These subjects were chosen at random. Table 1 classifies the contents of the dataset.

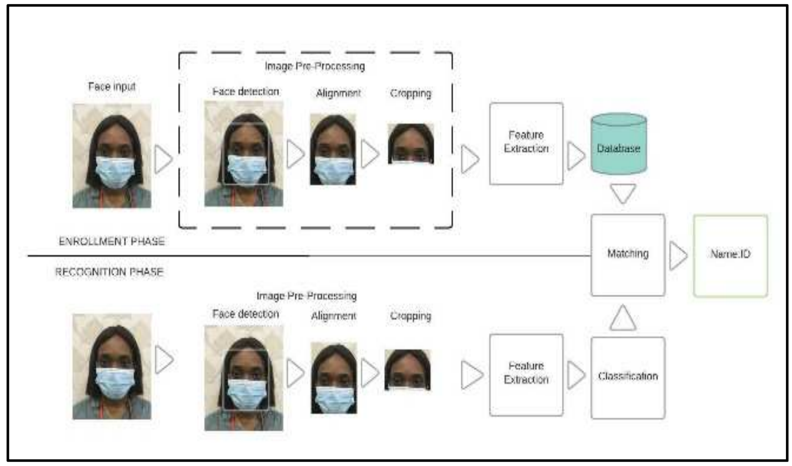


Fig. 1. Conceptual Framework of System

(a) (b) (c) (d)

Fig. 1a-b. Sample of face images acquired

- Datasets

The target group captured was final year students of Covenant University between the ages of 18-and 24. The dataset is made up of 200 subjects-male and females. These subjects were chosen at random. Table 1 classifies the contents of the dataset.

TABLE I. GENERATED DATASETS PROPERTIES

| Properties | Description |
|---|---|
| No. of Subjects | 100 |
| No. of images | 200 |
| No. of males | 50 |
| No. of females | 50 |
| No. of Images per subject | 2 |
| Gray/Color | Colour |
| Static/Video | Static |
| Face pose | No pose variation (looking straight at the camera) |
| Accessories | None |

- Image Pre-Processing

After the image is acquired, specific image processing steps are taken to process images. These include:

i. Face Detection

First, the face area is detected using the contour algorithm in the image. The shape of the face is mapped out, stating that this is indeed a human. Then using the Yolo V2 algorithm, coordinates x, y, w, and h are given to the image, creating a bounding box that shows the region of interest (ROI) in the image. The bounding box indicates the position of the human face.

Yolo stands for "You Only Look Once". It is a state-of-the-art machine vision object detection algorithm that can also be used for human face detection. This was developed in 2017 as an improvement over the initial YOLO model. This YOLOv2 is much faster than its predecessor. It can detect objects in video frames of up to 40 frames per second. Although we're not working with videos, its speed is instrumental in this research as it would be applied in real-time scenarios.

Many convolutional neural networks are used in the YoloV2 method, resulting in a Deep CNN model, as shown in Figure 3.

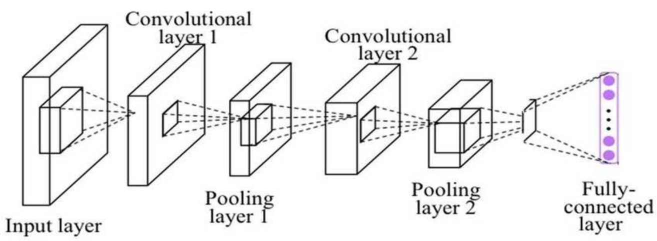


Fig. 3. Deep CNN Architecture

ii. Alignment

By adjusting the location of the eyes and setting the center of the eyes to specific pixels, the face image is straightened and aligned into place.

iii. Image Cropping and Resizing

The image region where the face can be found is then cropped, and only this region is used in the face recognition process. After that, the new image is normalized to a standard size of 64 x 64 pixels

- Feature Extraction

The KPU is the processor of the K210 chip. A neural network processor performs convolutional neural network calculations for feature extraction. It can acquire the size and coordinates of faces in real-time, as well as to detect and classify faces.

This model extracts the key features from an image, in this case, a face, and outputs a 128-feature vector. The network takes in a human face image and uses deep learning to calculate real attribute vectors. The image is sent into the neural network, which creates a face embedding the represented section. This method seeks to make a person's image ($x_1$) closer to all their images ($x_t$) and further away from others ($y_1$). It takes a 64x64 pixel image as input and generates a vector of 128 elements known as feature embedding

- Recognition Phase
- In this phase, an image is placed in front of the HuskyLens camera again. If a facemask is detected, the device runs through its memory to check if the facial features in the face image have already been learned. If it has, then the device would display the face ID of the individual on the serial monitor.
- Otherwise, it would learn the face of the image placed in front of it and assign an appropriate name ID to the image to be recognized.
- Otherwise, the steps mentioned above in the enrollment phase are repeated, and then the extracted feature patterns are compared to those already in the system database to see if there's a match.
- If there is, then the face ID of the person whose image is being recognized is displayed. The system flowchart is as shown in Fig.4.
- This research implementation entails the integration of the hardware and software that make up the system. The implementation of this study was done based on the system design as fully explained in Figure 4.
- The hardware was made-up of a Vero board. The construction of the hardware part involves connecting the HuskyLens module on a breadboard to the microcontroller, Arduino pro-mini. The hardware was implemented on a breadboard before it was integrated onto a Vero board.

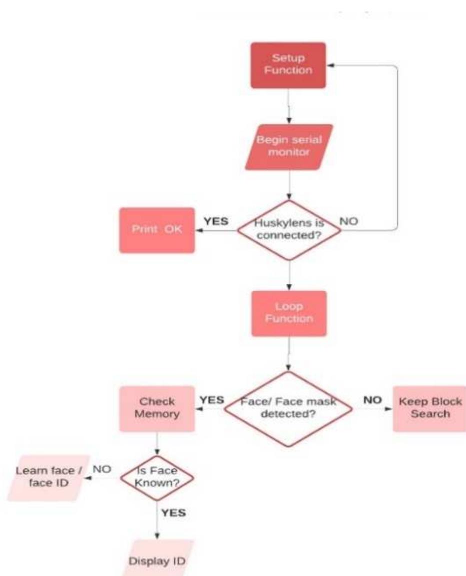


Fig. 4. System Flowchart

Using the Arduino, the Husky lens is programmed to assign names to the test images, and also to function as a stand-alone IC; a 100nF capacitor is connected from the reset pin to the chip select pin of the serial peripheral interface (SPI).

Next, the Arduino IDE was used to implement some lines of code to get the bounding box that would indicate face detection. An arrow is displayed on a face that is not recognized. If the object sensed is not a face, it returns '*object unknown*' to the serial monitor screen.

## IV. EMBEDDED SYSTEM IMPLEMENTATION

### A. Kendryte 2K10 Chip

At the very core of this work is the Artificial Intelligence (AI) on-chip design from Kendryte K210, as shown in Fig. 5.

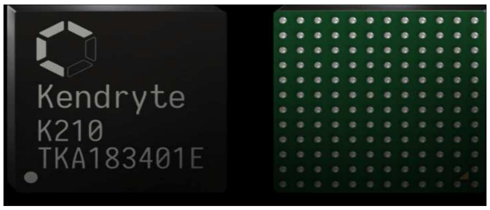


Fig. 5. Kendryte K210 chip

K210 is a powerful, cutting-edge computer chip designed for both visual and somatic recognition. In this design, its face detection and recognition properties were utilized. Also, its very low power consumption rate comes in very handy.

This microcontroller has a KPU (self-development network hardware accelerator) that can conduct high-performance convolutional neural network (CNN) operations.

### B. Huskylens AI Vision Kit

The HuskyLens device, as shown in Fig. 6, is a smart, easy-to-use AI vision sensor.

TABLE II. CONFUSION MATRIX, PERFORMANCE EVALUATION

| *Metrics* | *Positive (1)* | *Negative (0)* |
|---|---|---|
| Predicted Positive (1) | True Positive (TN) | False Positive |
| Predicted Negative (0) | False Negative | True Negative |

It supports AI machine vision due to the K210 chip embedded in it. The seven built-in functions of the device are face detection, feature extraction, object tracking and recognition, line tracking, color recognition, and tag recognition. New faces may be learned and identified simply by placing themselves in front of the camera and pushing the learning button.

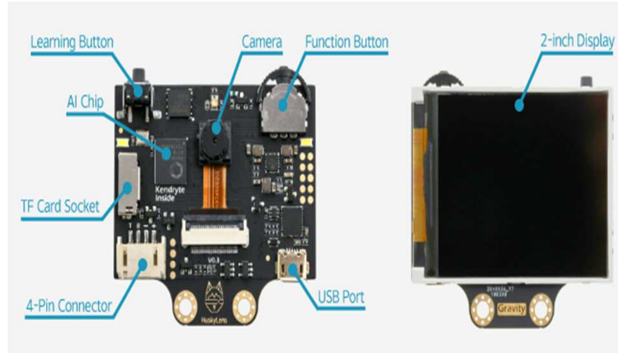


Fig. 6. HuskyLens Module

The Arduino Pro-mini is a microcontroller development board based on the ATmega328P microprocessor, a high-performance 8-bit AVR RISC-based microcontroller. It has a total of 14 digital input/output pins, a 16MHz ceramic resonator, a total of 6 analog input pins, and a power jack. It runs on 5 volts and connects to a computer via a USB connector. The board is controlled via Arduino IDE, an open-source environment where codes are compiled and uploaded onto the Arduino.

### C. System testing

For a biometric system, there are two possible outcomes-positive and negative. The positive result indicates a match when the face is compared to those present in the database, and a negative result indicates a mismatch. The positive outcome can be designated as "1" and the negative outcomes designated as '0".

To evaluate this design, a confusion matrix, performance evaluation technique is utilized as shown in Table 2. It has four possible outcomes: True positive, True Negative, False positive, and False-negative.

i. True Positive (TP): To obtain a true positive result, a positive value is correctly predicted as an actual positive. The model precisely matches the face input to the face enrolled in the database.

ii. True Negative (TN): If the actual truth is negative and the system correctly predicts the result as a negative, then this is referred to as a true negative. This means that the face is not enrolled in the database, and the system shows that.

iii. True Positive (TP): To obtain a true positive result, a positive value is correctly predicted as an actual positive. The model precisely matches the face input to the face enrolled in the database.

iv. True Negative (TN): If the actual truth is negative and the system correctly predicts the result as a negative, then this is referred to as a true negative. This means that the face is not enrolled in the database, and the system shows that.

v. False-Positive (FP): This is known as a Type 2 error. Here, the system incorrectly predicts a positive value. The face input is not enrolled in the database, but the system incorrectly matches with a face already enrolled in the database.

vi. False-Negative (FN): This is known as a Type 1 error. If the actual truth is positive, the system predicts the result as negative. The face input is enrolled in the database, but the system fails to recognize that individual.

The accuracy of the system is given by Eq.1:

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

Other performance metrics include:

True Positive Rate (TPR): This is also known as the sensitivity of the system. It is the proportion of faces that are correctly identified by the system. It is given by Eq.2:

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

False Positive Rate (FPR) –also known as a False Match rate (FMR). The probability of a decision stating that two faces are a match when they are not is known as a false match rate. In other words, It is the proportion of faces that are incorrectly identified. It is given in Eq. 3

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad (3)$$

True Negative Rate (TNR): Also known as Specificity. This is the proportion of faces that are not enrolled in the system and are correctly not identified by the system. As shown by (4)

$$\text{TNR} = 1 - \text{FPR} \quad (4)$$

False Negative Rate (FNR): Known as 'Miss Rate'. It is the proportion of enrolled faces that are incorrectly identified by the system. It is given by Eq.5:

$$\text{FNR} = 1 - \text{TPR} \quad (5)$$

Precision: This is the proportion of positive IDs that are correct, as shown by Eq.6

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \quad (6)$$

## V. RESULTS

Fig.7 and Fig.8 depict graphical results representations of the system performance on the masked and unmasked face, respectively. The TPR, FPR, TNR and FNR of the masked face recognition are 95.6%, 11.54%, 86.46 and 8.33% respectively. While the TPR, FPR, TNR and FNR of the masked face recognition are 95.6%, 4.17%, 95.83%, and 4.4% respectively. Comparing the masked and the unmarked face recognition system results, the variation in in term of the TPR and TNR are 4.1% and 9.7% relatively. This implies that the accuracy of the system to recognize the individuals wearing masks is very recommendable. The system is able the close the gap between intra-personal variation as regard masked face recognition system.

Fig. 9 depicts the overall masked and unmarked face recognition system performance, which are 90% and 94.7%, respectively.

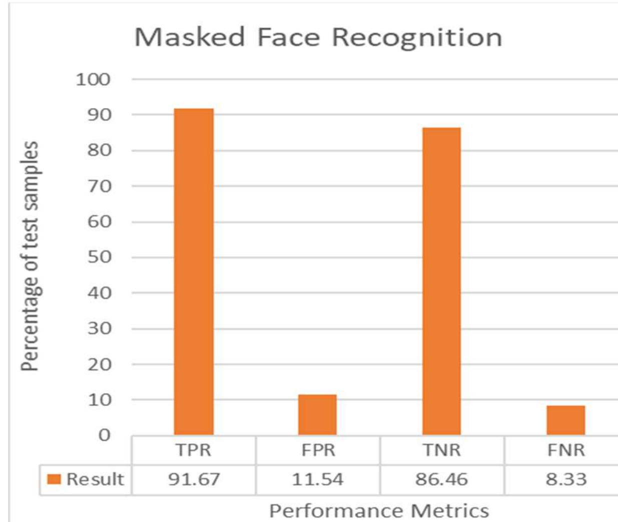


Fig. 7. Graphical representation of system performance on masked faces

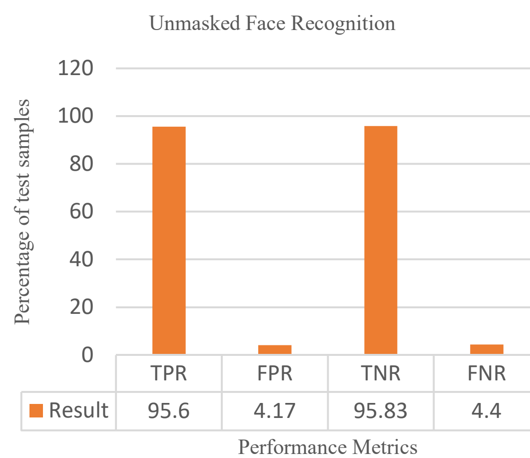


Fig. 8. Graphical representation of system performance on unmasked faces

Overall system performance is as shown in Fig.9.

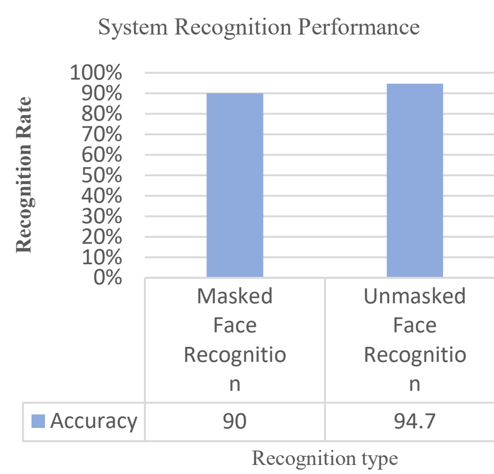


Fig. 9. Graphical representation of overall system performance

## VI. CONCLUSION

In conclusion, it was observed that the variation between masked and unmasked is relatively small. This means that system accurately recognized individuals even while wearing face masks. Therefore, the goal of developing and implementing an embedded masked face recognition system using Huskylens sytem-on-chip module that is capable of masked face recognition has been achieved. This research work is also helpful for real-time applications of masked face recognition, given the present pandemic crisis and law of waering of face maked in public places.

## VII. ACKNOWLEDGEMENT

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