



**GRADUATION PROJECT I REPORT
TOWARDS INFORMATION PROTECTION USING FACIAL AND GESTURE
RECOGNITION**

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ABSTRACT

In today's digital environment, data protection is one of the most sought-after industries. Information must be safeguarded to prevent third parties from misusing it for fraudulent purposes, such as phishing schemes and identity theft. Information security is achieved using security solutions, encryption, and other technology, as well as policies and processes. A typical system has many levels of protection ranging from physical to data-oriented to access and authorization control.

In this project, we plan to incorporate computer vision techniques to carry out the authentication and authorization techniques. In online security systems, both authentication and authorization are critical. They verify the user's identity and enable them access to your website or application. We want to employ facial recognition for authentication, and after the user has been validated, he will be granted access to his account. The user's face will be always monitored during their contact with the App to ensure that the user is still present. The session information and the user's face will be constantly watched to prevent an authenticated user from leaving the chair and an intruder from gaining access to the account. In terms of authorisation, we intend to establish gesture-based clearance systems that follow the nomenclature used by the United States Department of Défense. Different hand gestures made by an authenticated system will take as different commands to switch the mode and let the user access his data objects whose sensitivity is lesser than the user mode. This can be helpful where in user must switch roles quickly on seeing someone approaching his desktop personally.

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1. INTRODUCTION

Cyber security refers to the collection of methodologies, technologies, and processes used to safeguard the confidentiality, integrity, and availability of computer systems, networks, and data from cyber-attacks or unauthorized access.

Cybersecurity is critical because it safeguards all types of data against theft and loss. Sensitive data, personally identifiable information (PII), protected health information (PHI), personal information, intellectual property, data, and governmental and industry information systems all fall under this category. As a result, if you are uninformed of the importance of cybersecurity and fail to take preventative measures, you will most certainly face difficulties. Even little issues can develop to situations that are not only difficult to settle but potentially put your or others' safety at danger.

Facial recognition technology gives your security system similar abilities to verify an individual's identity by examining their face. This technology can be leveraged to identify people in videos and photos in real-time, as well as it uses biometrics to map faces and save recognizable features as verifiable data. This is an effective way to verify anyone's identity.

Besides having facial recognition, gesture recognition is as important as facial recognition, it is a technology aimed at providing live-time data to a computer to execute commands the user wants. The camera's motion sensor can perceive and interpret the person's movements as the primary source of data input.

Having both facial & gesture recognition can help offer safety and security to the organization, not only be that, but it can also provide authentication and authorization to protect your organization's information which is one of the most sought out fields in the current digital world. The purpose of this report is to illustrate the system which we've created which implements facial and gesture recognition, alongside customized forms and databases.

the proposed system provides authentication by using facial recognition in which the user is verified, he is provided access to his account. At all points of user interaction with the App, the user face will be monitored to make sure that the user is still around. The session details and the user's face will be monitored constantly to avoid any case of an authenticated user moving from the chair and intruder trying to access the account. The system also provides authorization by using gesture-based clearance systems. Different hand gestures made by an authenticated system will take as different commands to switch the mode and let the user access his data objects whose sensitivity is lesser than the user mode. This can be helpful where in user must switch roles quickly on seeing someone approaching his desktop personally.

CHAPTER – I
LITERATURE REVIEW

This chapter provides an extensive review of related works in the fields, all the works were segregated. subsection 2.1 talks about the work of gesture recognition, the second section 2.2 talks about facial recognition.

2.1 Gesture recognition

Su M [1], proposed a set of augmented reality assistance systems which was built on smart glasses as a human-machine interface. It allows users to experience the system from a personal perspective through the pointing gestures that can show the relevant information of the object pointed by the finger and the corresponding virtual tool. Its proposed methods including pointing gesture capture, finger-pointing analysis, and virtual tool positioning and rotation angle are developed.

Sharma [2], Talked deeper about the learning-based convolutional neural network (CNN) model is specifically designed for the recognition of gesture-based sign language. hand gesture recognition technique is presented for vision-based recognition of sign language. For this, a deep learning-based G-CNN model packed with compact representation is proposed, and 2 other architectures VGG11 and VGG-16 have been also examined and modified for the classification of sign language hand gestures.

Authors in [3], The main purpose of this paper is, to implement the RNN model based on LSTM, Convolution Peephole LSTM, and GRU, which are used to train SEMG benchmark databases and find the correlation between the input SEMG and outputs gesture. assessments are carried out on the most popular benchmark datasets called NinaPro, Electromyography-EMG, and UCI HAR Datasets. The convolution LSTM model achieved max training precision.

Mahmoud A.G[4], discussed the CNN framework with multiple layers for accurate, effective, and less complex human hand gesture recognition has been proposed. The framework includes two main phases: feature extraction and classification. These phases include multiple layers, each of which was designed to obtain the best results for human hand gesture recognition. Extensive experiments prove that the proposed system provides excellent results of accuracy, precision, sensitivity, and F1-score.

Tan in [5], EDenseNet is proposed for vision-based static gesture recognition. Talks about the importance of dense connectivity in dense blocks facilitate strong feature propagation and gradients flow in the network and the feature reuse eliminates the need for replicating features from earlier to latter layers., to improve the effectiveness of data shortage to improve generalization, several data expansion techniques are proposed for increasing the quantity and enhancing the variety of the training data.

M. Verma [6], hand gesture recognition (HGR) allows machines to identify hand gestures and execute the relevant action. There is a need to amalgamate HGR with AI to design and develop touch-less interfaces. We propose a light-weighted end-to-end shallow network for HGR systems. Fit-Hand outperformed Deep Gestures and DeepConv HGR models over MUGD, Finger Spelling, and HANDS in terms of recognition accuracy over two experimental setups. The proposed framework is robust to all kinds of challenges presents in the HGR, which reflect the efficacy of the model to real-life applications.

E. Niloy [7], found that the system must be intelligent and powerful enough to detect, match and predict a character and the hand contour is drawn and the center of the palm is calculated using the Euclidean distance method. The system uses OpenCV's line drawing function to draw the tracking path, which in terms then is used to detect and recognize the character. The experiment was conducted on an Intel Core i5-8250U 1.8GHz CPU with 8GB of RAM and 2GB of NVIDIA MX150 GPU card. The model was trained with a total of 23,040 images of the numerals and characters using Keras's image data generator.

Authors in [8], In the data acquisition phase where the grey scale data of static signs are gathered employing high-quality camera images. The sign language recognition scheme follows four different phases, namely data acquisition, pre-processing, training the data set, and testing through CNN classifier. Dataset has different static signs which are gathered in the form of grey scale images. The image augmentation process involves expanding training images to create a modified image version. The accuracy of these modified images increased by 99.27% and 98.7% for sign language recognition, respectively.

Authors in [9], This SLR system was able to recognize 26 Indian Sign Language gestures and used Principal Component Analysis (PCA) during the classification stage. Sign Language Recognition Systems (SLR) have two main types - wearable and video-based. The design of the sign language recognition system itself is a multi-step process. The first of these is the sign language recognition system itself. The components for the sign language recognition system can all be found in the same directory. The system's real-world function is to allow for real-time gesture recognition. A bespoke CNN will be created for the system which will not have been pre-trained on any previous data.

Authors in [10], Sign language research aims to help the hearing impaired understand what healthy people say. The system uses American sign language and Arabic numeral gestures for model training. It also recognizes the user's voice or text converted to the corresponding English in sign language. The system is based on computer vision with four main features. The project builds Inception and V3 in the TensorFlow environment extracts image features from the ASL dataset.

Narayan [11], System recognizes gestures given by only one hand, which it takes images data using the webcam of the computer, then pre-processing of the image is done using masking technique which is done with the Python programming Language using the CNN and it has three layers (Convolutional, Max-Pooling and Fully Connected), and masking technique for image pre-processing with the help of OpenCV module in python. An image that is given as input is predicted and the translation is done in the form of text, then converted to the audio used American Sign Language (ASL).

Nair [12], Hand gesture recognition is broadly categorized into a 3-D model-based and appearance-based and is categorized into (3-D volumetric, 3-D Geometric, 3-D Skeleton, and hand shape according to the skeletal joints of a human hand). The components of the architecture model are: (1. Detector: observe the presence of a gesture in the frames of images provided as input, 2. Classifier: classify the gestures according to the training set data, 3. Post-Computational Services, 4. Single-Time Activator: achieved, 5. Extraction of Gesture Using Open Pose, 6. Multi-Stage CNN Working).

Authors in [13], Convolutional neural networks can be used to accurately recognize different signs of sign language. This generalization capacity of CNNs (using the Microsoft Kinect) in spatiotemporal data can contribute to the broader research field on automatic sign language recognition. The artificial neurons in a CNN will connect to a local region of the visual field, called a receptive field. For the pooling method, we use max-pooling.

Nandhini [14], Deep learning to know is a department of device attending to know that's primarily based totally on synthetic neural networks, to classify and detect the activity accurately, pre-trained models like CNN models are trained and accuracy can be obtained. The 4 phases of proposed methodologies are divided as: (1. Prepare dataset, 2. Frame Extraction and pre-processing 3. Model construction, 4. Model training and testing).

McCleary [15], A database of four different BSL hand gesture motions are presented in the form of micro-Doppler signals, recorded with a continuous waveform radar. For detecting the presence of the micro-Doppler signatures, joint time-frequency is applied by calculating their spectrograms. Each gesture is expected to contain unique spectral characteristics that are exploited to classify the novel explainable AI algorithm is implemented to give the user visual feedback, in the form of color highlights, for the most relevant features used to classify each signal. Around nine billion individuals are hard of hearing and unable to speak. Since ordinary individuals are not trained on gesture-based communication, at the time of crisis passing on their message is troublesome. The Convolutional Neural Network (CNN) is used to train the model on different hand gestures. In this paper, they introduced an algorithm to recognize the Indian Sign Language (ISL). In their strategy, they have utilized 26 signs which address the situation of each of the five fingers. Key points are mapped using SIFT algorithm which represents a sign language. they introduced the different strategies for Hand motion and communication through signing acknowledgment. Various types of calculations are utilized to catch the signal and stance of the hand. This is helpful to remove the mathematical element which is important to frame a hand shape.

Authors in [16], Sign Language is used by the deaf and voiceless to communicate with others. The main motive behind this system is to bridge the communication gap between the communities. Algorithms such as KNN, SVM, and CNN models were used to solve the problem. American Sign Language was created back in 1817 for deaf students. It was an attempt to represent the syntax and structure of the English language in the hands of students. By the year 1835, ASL was used as the language to instruct and communicate with the student in schools. Software is a system that serves as a translator and helps in understanding sign language by converting it to text and speech. It can also help someone with a voice to communicate with those who only understand hand sign language. With the help of the embedded camera, microphone and speakers, the system will capture real-time gestures and convert them to speech and text. K-nearest neighbors (KNN) is a classification technique that uses the vector space model to classify data points. The array of the image is classified according to most of the classes those k points belong to. The parameter k is always preferred to be an odd number since it would make the voting process easier. Choosing a small value of k means that noise will have a higher influence on the result.

Authors in [17], We employ a pose-driven spatial attention strategy, which guides our proposed Static and Dynamic gestures Network—StaDNet. The Convolutional Neural Network (CNN) in StaDNet is fine-tuned on a background-substituted hand gestures dataset. It is utilized to detect 10 static gestures for each hand as well as to obtain the hand image-embeddings. Moreover, we transfer the knowledge learned through the proposed

methodology to the Praxis gestures dataset, and the obtained results also outscore the state-of-the-art on this dataset Automatic hand sign language identification from visual data is performed using the Restricted Boltzmann Machine (RBM), a deep learning technique. We examine how RBM, as a deep generative model, can generate the input data's distribution for improved recognition of unseen data. The model input considers two modalities, RGB and Depth, in three forms: original picture, cropped image, and noisy cropped image. The hand of these cropped photos is recognized using a Convolutional Neural Network on five crops of the input image (CNN). Following that, for each modality, three types of detected hand pictures are created and fed into RBMs. The proposed multi-modal model is trained on all and part of the American alphabet and digits of four publicly available datasets. It achieves state-of-the-art results on Massey University Gesture Dataset 2012, American Sign Language (ASL), and Fingerspelling A dataset.

Bhadra [18], Nowadays, automatic recognition of sign language from hand gesture pictures is critical. People with hearing and speech disorders can benefit from the accurate detection and categorization of sign language. A deep multi-layered convolution neural network is suggested in this study for this purpose. In the deep multi-layered CNN structure, 32 convolution filters with 3 x 3 kernel, LeakyReLU activation function, and 2 x 2 max-pooling operation were used in the suggested technique. In the output layer, the SoftMax activation function was utilized. The suggested method was tested using a database of hand gesture pictures that were both static (54000 images and 36 classes) and dynamic (49613 photos and 23 classes). The suggested methodology's efficacy in detecting sign language is demonstrated by experimental findings.

Table 1.1 Gesture recognition, demonstrate the techniques of each application, its performance, how it works, it's the dataset, how the applications came out, drawbacks, and what can be done in the future.

Table 1.1 gesture recognition

Application	Technique	Dataset	Performance Metric	Result	Drawbacks	Future Work
Smart training: Mask R-CNN oriented approach [1]	R-CNN Mask R-CNN YOLO SSD	The convolution layer is the core part of the network, creating different representations of the learning dataset, starting from more general ones at the first larger layers, becoming more specific at the deeper layers	the client uses the Moverio BT-300 smart glasses developed by EPSON, and the server developed using Unity. It is the core algorithm which performs object detection, pointing analysis, and virtual tool positioning and rotation angle analysis operations.	show the relevant information of the the object pointed by the finger and the corresponding virtual tool.	object recognition in weak light conditions still reaching 79%. skin color can be extracted, it is still affected by light. When facing insufficient light, it may affect gesture detection. affect the results for	pre-processing may need in the future to overcome the light problem. do video and real-time implementation

					the pointing analysis when wearing accessories on hands such as rings, watches, bracelets. improvement for gesture capture due to the error between the analysis angle and the actual angle less than 1.32 degrees.	
Vision-based hand gesture recognition using deep learning for the interpretation of sign language [2]	LSTM SVM Dual-Hahn and krawtchouck. RNN	24 and 36 static gesture of ASL. 100 isolated signs of ISL. Chinese Sign Language	The performance of this work is tested for the self-collected 43 distinct ISL gestures and publicly available ASL dataset. the G-CNN model achieves the highest classification accuracy of 94.83%, 99.96%, and 100%	ability to recognize the complex signs of ISL with good recognition results over the state-of-art approaches	the error rate in real-time recognition of sign language	the architecture of these deep learning-based models can further be optimized for hand gesture recognition and more detailed comparison can be made.
sEMG pattern recognition based on recurrent neural network [3]	LSTM, Convolution LSTM.	Electro-Myography-EMG-Dataset. UCI HAR Dataset. Ninapro DB2. NinaPro, Electro-Myography-EMG.		demonstrated three LSTM models tested on different datasets with different parameters as the	additional challenges will arise due to a variety of factors, including signal instability, mechanical design, encoder accuracy,	concentration on low-cost implementation and testing of the suggested above-

				number of electrodes, output gesture, several elements, and electrode placement. The minimum training classification loss factor reached 0.074. The minimum number of an electrode placed on the forearm/leg to give the best results are eight	data gathering, and motor torque.	knee exoskeleton model.
Convolutional neural networks framework for the human hand gesture recognition [4]	CNN	Self-acquired dataset (more than 55000 images). ASL dataset (36 gestures from 5 subjects). Hand-based near-infrared dataset (20000 images for ten kinds of gestures). CGD dataset (50000 images for 249 kinds of gestures).	system performance was evaluated on 36 gesture poses using the American sign language (ASL) dataset, and the obtained average accuracy was 87.83%.	An accurate and effective deep learning framework is proposed for recognizing static hand gestures based on CNN. the comparison between the proposed system and other	Has a low illumination	the proposed CNN framework will be prepared to be utilized for recognizing dynamic gestures.

				related works proved that the proposed system is more effective and accurate than others.		
Hand gesture recognition via enhanced densely connected convolutional neural network [5]	image processing. 9 data augmentation .	ASL ASL with digits NUS hand gesture	demonstrates the effectiveness of the data augmentation techniques proposed, and also substantiates EDenseNet's superiority in comparison with other recent deep learning-driven instances.	Training the network with augmented data resulted in improved recognition accuracy across the board.		
One for All: An End-to-End Compact Solution for Hand Gesture Recognition [6]	glove-based techniques and vision-based techniques: hand and appearance-based model. 3D hand-based models	MUGD-I, MUGD-II, MUGD-III, MUGD-IV, MUGD-V, Finger Spelling and OUHANDS	-some other HGR approaches have achieved good results - the robustness of Fit-Hand to extract edges of hand postures and surpass the background information. - Fit-Hand does not need hand segmentation. Fit-Hand can easily learn the features from segmented or black and white hand gesture images. There, we conclude that FitHand is a generic HGR framework that is capable to learn features in practical scenarios.	proposed a one for all: end-to-end compact solution named as Fit-Hand: fine-grained feature attentive network that contains two main blocks: FineFeat module and dilated Conv layer	1-the performance of HGR influenced by various aspects such as illumination variations, cluttered backgrounds, spontaneous capture, etc. 2-The existing approaches needs expert expertise as well as auxiliary computation at stage 1 to remove the complexities from the input images	they propose a novel end-to-end compact CNN framework: fine-grained feature attentive network for hand gesture recognition (Fit-Hand) to solve the challenges

Hand Gesture-Based Character Recognition Using OpenCV and Deep Learning [7]	uses OpenCV's line drawing function to draw the tracking path, which in terms then is used to detect and recognize the character. And use deep learning	There is a total of 36 classes (0-9 and A-Z). Each the class has 520 images for training and 120 images for testing.	the performance is evaluated in terms of accuracy and loss. the accuracy and loss are calculated while the model is trained and validated after each cycle.	propose a new way to achieve hand gesture-based character recognition by using simple cameras. To remove the dependency on special sensors and other hardware	Fast, accurate, and user-friendly human-computer interaction requires both processing and intelligence. Understanding signs and symbols are already possible by computers but recognizing symbols drawn live by a human in front of a camera is still a new concept	evaluate our model with another state of the art models, especially in the field of hand detection and tracking in the future and create a baseline on which we can improve in the future
HAND GESTURE RECOGNITION FOR DEAF AND DUMB USING CNN TECHNIQUE [8]	the sign language is converted into text using Convolutional neural network-based Deep learning model. a total of 3500 static sign images of 10 (Indian sign language) static signs are gathered from various impaired humans. A total of 4 layers and 16 filters were used in Convolutional Neural Network (CNN) Architecture	using convolutional neural networks to identify the static signs of ISL (Indian Sign Language).	the system can be tested in the CNN architecture by using different frames in the videos. The accuracy of the testing and validation is further improved by increasing the number of filters.	CNN model with 4 layers and 64 filters has been used for training the ISL data set. Thus, the model is used to recognize the ISL hand gestures.	Identification of human signs fully in automatic mode is an interdisciplinary problem	few researchers are following deep learning system to recognize human signs, microwave imaging, and Standard CT/MRI imaging systems.

: A CNN sign language recognition system with single & double-handed gestures [9]	python programming language/Tensorflow/Keras/OpenCV/NumPy/OS module	A bespoke British Sign Language dataset containing 11,875 images - is then performed to train and test the CNN which is used for the classification of human hand performed gestures	the testing of the trained CNN using the testing dataset is useful for providing an insight into the effectiveness of the model. Therefore a further series of tests have been carried out on the system to determine its robustness as a real-time sign language recognition system.	the graphical user interface was implemented using the OpenCV library and it has the original frame in its entirety, with a red box in the top left-hand corner. The red box represents the region of interest and in the area in which the user must perform the gestures	communication gap that exists between the hearing and hearing-impaired community	SLR systems bridge this gap, bespoke British Sign Language gesture dataset. The system was designed to be able to recognize 19 British Sign Language gestures
Sign Language Recognition Based on Computer Vision [10]	The system uses American sign language and Arabic numeral gestures for model training//uses THE CNN neural network to extract the characteristics of the ASL data corpus, and then puts it into the LSTM classifier	Each picture size is 200 x 200, after downloading, trim the dataset, extract the image of the hand area, and then divide them into training, testing, and validation sets.	Experiments test sign language recognition accuracy of 95.52%, sign language translation accuracy of 93.3%, to meet basic needs, for the hearing-impaired groups to open the door to communication.	1-uses THE CNN neural network to extract the characteristics of the ASL data corpus, and then puts it into the LSTM classifier to realize the recognition of character-level sign language	Sign language used in daily life is very complex, in different language environments, the same sign language may have many different meanings	consider the environmental characteristics of sign language use, to improve the accuracy of sign language recognition, better suitable for the real-life environment.

				<p>2- enables the translation of sign language through the system</p> <p>3- can convert user text or speech input into the corresponding American sign language or Arabic numeral sign language</p>		
Sign Language Recognition Using Deep Learning. [11]	<p>Deep Learning Techniques.</p> <ul style="list-style-type: none"> - Photograph and computer vision techniques. - Sign Language using machine learning techniques. 	Is the video dataset of sign words, with the variability through acting the gestures and may be used to build ordinary deaf human's interfaces.	CNN works with performance and also with a minimal number of training samples.	The setup machine can record Sign videos and it is considered and then extraction of frames is done, then CNN model takes the frames as input to detect Sign Language Words.	To scale back such sorts of problems all the datasets should be collected in the experiment should be colored with a bolt of Daily lightning during an indoor environment than an outdoor environment.	Propose a three-dimensional CNN version and display that the massive amount of data offered to computer vision.
Hand Gesture Recognition using Double CNN and Transfer Learning. [12]	CNN, Hand gesture recognition techniques, Hand-skeletal joints technique.	For the detection of the gesture, we employ Double-channel CNN over a smaller part of the dataset to detect the presence of the gesture. - Ego Gesture and NVIDIA Dynamic Hand Gesture	Investigated hand gesture sequence classification tasks. - The classifier will be activated when it detects an input frame. This reduces a lot of	Since they ran the model on a low-end machine without using external hardware	System requirements in The classifier are large compared to other models. - High power and memory consumption	Precomputed images can be added to the dataset to reduce noise in data.

		<p>Datasets are used to evaluate the architecture.</p> <ul style="list-style-type: none"> - 3D filter is applied to the dataset using 3D convolutions. - Sign language digits and Thomas Moeslund's gesture recognition. - DHG dataset. 	<p>computational time and achieves high performance.</p> <ul style="list-style-type: none"> - The performance of the proposed model majorly relies on the detector. 	<p>, the results could be considered good enough on a challenging dataset.</p>	<p>by The classifier.</p> <ul style="list-style-type: none"> - Integration with the hand-skeletal joints technique resulted in lower accuracy. - Accuracy may be High but it doesn't employ CNN which makes The computation time very high. - Replacing the original frame sequence with the key frame sequence results in more computation time. 	
Hand Gesture Recognition for Sign Language Using Convolutional Neural Network. [13]	CNN, Masking technique, HOG technique.	<p>The alteration in the kernel size can be inspired by the dataset which includes the background, preprocessing can be done to remove the background and is split into 3 sets, training, testing, and validation.</p>	<p>In different situations, a general invariant method is needed. Deep learning has been performing well in recent years mainly in computer vision problems.</p> <ul style="list-style-type: none"> - GPU architectures and their design. 	<p>The input image is in the form array of pixels format, it is given to the first layer that is convolution layer, which applies a filter to the input image that gives the result as activation, by applying same filters repeatedly to the input gives the</p>	<p>The drawback for the deaf is their employment issues. Communication has always been a prominent part in getting the task solved this system can help in solving the issue of unemployment for the deaf.</p>	<p>Recognition of gestures that are made with both hands because recognizes gestures given by only one hand in the system also would use signs of common words so that it is easy to form a</p>

				activation map that is called as a feature map.		sentence for future work.
Sign Language Recognition Using Convolutional Neural Networks.[14]	Sliding windows technique. - Pooling scheme. - CNN.	20 different Italian gestures, performed by 27 users with variations in surroundings, clothing, lighting, and gesture movement.	Convolutional neural networks can be used to accurately recognize different signs of sign language.	The test result is higher than the validation result because the validation set doesn't contain users and backgrounds in the training set.	There is an undeniable communication problem between the Deaf community and the hearing majority. Innovations in automatic sign language recognition try to tear down this communication barrier.	This Generalization capacity of CNNs in spatio-temporal data can contribute to the broader research field on automatic sign language recognition.
Sign Language Recognition using micro-Doppler and Explainable Deep Learning. [15]	CNN.	ImageNet dataset. - BSL signs were recorded using a portable Continuous Waveform (CW) radar with a carrier frequency equal to 24GHz.	Evaluate the classification, when comparing the relative performance of different classifiers with their values for precision and recall, the need for a single metric appears.	In the case of this dataset, there were several times, approximately a quarter, where the highlight covers the noisy background of the spectrogram rather than the microdropper response. In most other cases, the highlight is partially	AlexNet was chosen as the pre-trained model for transfer learning and a few modifications were made to adapt it to the problem of SLR.	Work can be proposed for recording data from different angles to add robustness to the system. If the network was to be tested on new data, the accuracy would drop significantly. - Implem

				overlapping or completely overlapping a feature in the microdropper signal such as peaks or particularly un-noisy portions of the signal.		ent an unknown class and see how the system would classify an unseen fifth gesture, as of now it would be wrongly classified into one of the existing classes.
sign languages and with their appropriate outputs would make the interaction between challenged people and normal people easy. [16]	Algorithms such as K-Nearest neighbors (KNN), Multi-class Super Vector. Machine (SVM), and experiments using hand gloves were used to decode the hand gesture movements before.	Each image is stored in a separate folder called a pickle file, and the labels are also done at the same time. For reading the dataset, each folder is opened simultaneously, and all the images are read in one go. The images go through the preprocessing stage and are stored in their respective pickle files.	the dataset increases SVM performs better than KNN,	training data but when coming to generalized data, it would give out poor results whereas underfitting results in poor results on both test and other data. To avoid these various methods were used in the system	faced problem here is that everyone around may not be able to understand sign language.	People can now exchange thoughts, ideas, and messages irrespective of the person's ability to understand and sign language. This system helps the communication between the speechless and the

						blind as well. Any person who is interested in learning sign language can also acquire it by using the speech-to-hand sign gesture mode.
perform automatic hand sign language recognition from visual data. [17]	PCA-CGP	network based Deeping learning model.	Improvement in performance of age estimation with RoR models.	For age estimation Guided CNN(AE-CNN) there's promising results on two well-known public domains.	Ordinal regression problems can be solved by using CNN.	Researchers at the University of British Columbia in Canada have proposed a novel approach to sign language detection, which could lead to more convenient detection of sign languages.
gesture images is crucial nowadays. Accurate detection and classificati	SIFT	36 classes (0-9 and A-Z). Each class has 520 images for training and 120 images for testing.	the performance is evaluated in terms of accuracy and loss. the accuracy and loss are	propose a new way to achieve hand gesturebased character		In this paper, we show how we can reduce the

on of sign language can help people with hearing and speech disorder. [18]			calculated while the model is training and validated after each cycle.	recognition by using simple cameras. To remove the dependency on special sensors and other hardware		complexity of training RBMs by defining simple simple RBM models that can share information in early training stages. We plan to extend model behaviour to deal with image sequences and model spatio-temporal information of sign gestures.
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The table above gives information about gesture recognition .in this table we Summarise the information by selecting and reporting application, technique, dataset, performance metric, result, drawbacks, features, and make comparisons where relevant. All these techniques It is often used for classification, identification, detection, and prediction applications.

Automating data-driven procedures is also incredibly efficient. The core concept is to utilize data to create a model that can output anything. With a fresh input, this output may provide a correct response or make predictions about known data.

Most of the application uses a Convolutional neural network (CNN) which is a neural network that has one or more convolutional layers and is used mainly for image processing, classification, segmentation, and for other auto correlated data. The creation of equipment like R-CNN, which are instances of innovation in input device technologies [2-6], was prompted by the progress of computing and the availability of access to new techniques. These technologies are therefore capable of recording human gestures, resulting in the development of a new medium of human-machine interaction. These devices are used in a wide range of fields, including sign language translation [12-15]. Methodologies for recognizing gestures are often classified into two categories: static and dynamic. The advantage of this strategy is the lower computing cost. Static gestures only require the

analysis of a single picture at the input of the classifier. Image sequence processing and more complicated gesture detection algorithms are required for dynamic gestures. Several recognition approaches based on supervised and unsupervised learning may be found in the literature. We may use neural networks [1–12], convolutional neural networks [13–18] as examples.

2.2 Facial recognition

Upadhyaya [19] Face recognition has been implemented and presented in this paper by using a Deep Neural Network. The authenticity problem can be handled by using either facial recognition or age prediction alone. So, first, this model detects the person's face, and then it predicts the person's age. If the individual is eligible to view the information or perform a task, their access will be limited; otherwise, their access will be restricted. So, it helps to solve two difficulties in this case: the person's identification cannot be faked, and their age is also confirmed by the system. (CNN for the face and technique for the age.)

Mishra.S,[20] This thesis work proposed a deep residual learning network to recognize human facial emotions which defines an approach to train a very deep network. ResNet50 with 50 layers is the base model for this thesis work and the performance is compared with Convolutional Neural Network (CNN). Two publicly available datasets CK+ and FER were chosen, and the performance of the network was compared using these datasets. The result of the proposed model shows that the deep residual learning network (ResNet50) performs better than CNN for facial emotion recognition in both FER and CK+ datasets.

Dliwati [21] This research aims for developing a security system that combines some recognition algorithms based on machine learning and deep learning techniques to verify the identity of each user “authentication” for the website and all the services associated with it. Thus, we can achieve the highest level of protection and security from the digital gaps that hackers may exploit. Therefore, facial expression became the most important technique to identify hackers. The obtained results reveal that deep learning-based techniques for face recognition over a collected dataset are superior to conventional machine learning techniques.

Hernandez-de-Menendez [22] Concerning Biometric technology is relatively new and has changed the way identification and authentication processes are performed. New characteristics are under development for commercial applications, such as vascular pattern recognition, ear shape recognition, facial thermography, odor sensing, gait recognition, heartbeat authentication, brain waves, and human body bioacoustics. The biggest challenge this technology must overcome is security and privacy issues, which must be addressed to fully develop the technology to its full potential.

Cirlugea [23] On the Android operating system, a biometric face recognition mobile phone application was built for authentication. The Android Studio IDE (Integrated Development Environment), Java programming, and Google's Mobile Vision API are used to create the app (Application Programming Interface). This application demonstrates that face recognition authentication may be implemented on any mobile phone with little computational overhead and without the need for expensive extra hardware.

Liu [24] When it comes to user authentication, biometrics are crucial. The most extensively used biometrics, such as a facial characteristic or a fingerprint, is, however, easy to capture or record, making them subject to spoofing assaults. Intracorporal biometrics, such as electrocardiography and electroencephalography, on the other hand, are difficult to gather and hence safer for authentication. Unfortunately, because of their sophisticated gathering techniques and restrictive limits on users, adopting them is not user-friendly. MandiPass is a revolutionary biometric-based authentication method that we propose. MandiPass collects intracorporal biometrics from the vibration of the user's mandible using inertial measurement units (IMU), which are frequently used in portable devices. For authentication, the user only needs to say a brief 'EMM' to generate the vibration. MandiPass offers safe and user-friendly biometric-based authentication in this way. We design a two-branch deep neural network for effective biometric extraction and theoretically evaluate the viability of MandiPass. To protect against replay assaults, we use a Gaussian matrix. MandiPass can achieve an equal mistake rate of 1.28 percent in a variety of challenging conditions, according to extensive trial findings with 34 participants. Inertial Measurement Unit, Biometrics, User Authentication, Deep Learning are all index terms.

Authors in [25] Authentication methods of the future need to maintain the ability to provide secure access without a speed reduction. Facial recognition technologies are quickly becoming integral parts of user security, allowing for a secondary level of user authentication. Augmenting traditional username and password security with facial biometrics has already seen impressive results. A Convolutional Neural Network (CNN) is a powerful classification approach that is often used for image identification and verification.

Authors in [26] Your Eyes Show What Your Eyes See (Y-EYES) is a software-based face PA Detection (PAD) method that captures corneal specular reflections using the front camera and analyzes them using lightweight Machine Learning (ML) techniques. It can be applied for multiple contactless biometric authentications accurately and efficiently without any costly extra sensors. Our extensive experimental results show that it achieves liveness detection with high accuracy at around 200 ms against various types of sophisticated PA.

Authors in [27] Deep learning is a branch of machine learning where algorithms are taught to identify patterns in vast amounts of data. the researchers trained and validated a deep learning model using 13,000 photos collected from Kaggle. The training accuracy of the

model was 95.72% and the validation accuracy was 96.27% - both impressive for a face recognition task.

Authors in [28] Face recognition has a very important role in various applications, from security, surveillance to authentication. For safety, most households is having CCTV cameras such that they could recognize the persons from them. The major objective is to recognize the faces of people from the video by HOG feature extractor and classify them using SVM and train the machine to tell who the person is working for the organization and who is the intruder.

Authors in [29], The anti-spoofing system is based on a proposed Convolution Neural Network (CNN) based architecture. The accuracy of the proposed system is 95%. It finds its application in verification, video surveillance, medical science, access control, law enforcement, and biometrics.

Anti-Spoofing systems have been developed based upon various existing models and algorithms such as Convolution Neural Networks. It uses a convolution neural network-based architecture to provide robustness against the most common spoofing ways. An eKYC system has been developed to detect spoofing attacks with an accuracy of 95%

K. M. Sagayam [30], The proposed approach adopts frameworks of deep learning, TensorFlow, Keras, and OpenCV libraries to detect face masks in real-time. Machine learning engineers have come up with several algorithms and techniques to identify unmasked individuals using various mask detection models. The data were trained and tested for the model to gain good accuracy while detection. This paper describes a new convolutional neural network architecture called MobileNet Convolutional Neural Network. The classifier's ability was determined by Recall and the measure of test accuracy plot was F1 score.

L. Liu, [31], PassFace is an anti-spoofing facial recognition system that verifies the smartphone for authentication as well as the second factor merely using raw facial videos without any user intervention. An anti-spoofing facial recognition system, PassFace, could achieve over 99% true acceptance rate (TAR) while maintaining less than 1% false acceptance rates (FAR), according to the authors. PassFace is an anti-spoofing facial recognition system that verifies a user's face and his/her smartphone used for authentication simultaneously.

A. Hassani and H. Malik [32], A spoof is an artificial representation of a human face designed to fool a facial recognition system. The mask spoof is designed to look like the face of an enrolled user and fool security systems. US National Institute of Standards and Technology has developed a series of standards for facial spoof presentation. Skin reflectance can provide low-cost systems that protect against even simple masks – but it also has the advantage of being cheap to manufacture.

W. Xu *et al.*[33], we try to defeat this problem by extracting both the 3D geometry and inner biomaterial features from RFID backscatter signals using COTS RFID systems. RFace extracts both the 3D geometry and inner biomaterial features of faces using a COTS RFID tag array. In this article, we propose a system called RFace, which can extract both 3D facial geometry and biomaterial features from RF signals. In RFace, we explore the possibility of

using RF signals to capture and extract the desired facial features from raw backscatter signals.

S. Pichetjamroen, [34], presents the implementation of a face time attendance system with an additional factor, a QR code to improve accuracy. This two-factor authentication system was developed in the form of a kiosk with a contactless process, which emerged due to the COVID-19 pandemic. The two-authentication methodology in this system is like traditional authentication with a username and password but instead substitutes a username with a user's QR code and the "password" was replaced by a user's face image in one-to-one identification.

Authors in [35] propose to enhance a common text password authentication interface to encrypted documents with a biometric facial identity verification providing a high-security mechanism based on pseudo identities. The paper also includes two contributions, the proposed scheme enables password autofill without referring to any external service, and the adoption of biometric verification techniques enabling fine-tuning of false acceptance and false rejection rates.

Authors in [36] This report describes a simple low-memory detection algorithm and demonstrates how it performs to emulate real-world scenarios in an experimental setup, which is proved to be fast, working well on single-board computers, and handling high-resolution video recordings.

Mohamed [37] The proposed approach in this paper is a deep learning technique which is a sequential CNN (convolution Neural Network) divided into a feature extraction stage and a classification stage. It also demonstrates the most widely used biometric approach is face recognition and one of these fields is mobile devices authentication.

Bhattacharya, [38] presents an approach to detect and identify a human face from the real-time video that tracks a face and compares it with stored data of known individuals. The approach recognizes an individual within a fraction of a second which completely ignores any background effect. This method works on different lighting conditions which make it suitable to execute its purpose in a wide variety of environments without encountering any significant error.

Authors in [39] This paper is aimed at developing an electronic payment system that integrates all the bank accounts of a particular holder together and access granted to them with or without a payment card through a multi-factor authentication procedure such as pin, fingerprint, iris, or 3D facial recognition. The system offers ease of use and simplifies the use of the platform to encourage financial inclusion in the country. aimed to define a safekeeping alert device spending little handling power by the Internet of things which help out to observer plus alerts when gestures or else motion are there then send images to a cloud server. There are two challenges such as the address of every device that should be stored and the second task will be recorded storing will be discussed in detail.

Table 2.2 Face recognition demonstrates the techniques of each application, its performance, how it works, its dataset, how the applications came out, drawbacks, and what can be done in the future.

Table 1.2 Face recognition

Application	Technique	Dataset	Performance Metric	Result	Drawbacks	Future work
A biometric verification facility for password autofill to protect electronic documents [19]	PGS JTR HC PCFG FYEO IODA FAR FRR	uses 39 datasets with random decimal digits.	The authentication performed by FYEO is contactless and yet involves data produced by a physical process filtered out with a complex non-linear filter	provides contactless authentication of legal users of the document based on their high entropy biometric data. the entire authentication process is truly offline hence no external server or database is needed	the state-of-the-art biometric recognition techniques do not necessarily comply with the irreversibility and unlinkability requirements for biometric verifiers	working towards a more secure transfer of electronic documents exchanged in collaborative processes by incorporating effective methods for determining the liveness of the subject in front of the camera
Face spoofing detection via an ensemble of classifiers toward low-power devices [20]	PLS SVM GPU MLP	All dataset videos are resized to 960×540 pixels, but keeping their original aspect ratio.	A cross-database investigation gives an insight into the generalization power of countermeasure algorithms which demonstrate the cross-testing performance metric for MLP, PLS, SVM approaches	able to achieve state-of-the-art performance on widely explored databases.	expressive advances in numerous areas of biometric science. lack of generalization in cross dataset settings. accuracy tends to reduce significantly, due to their inherent	add extra feature descriptors, including another relevant spoofing datasets and learn spatial-temporal representations.

					bias	
Face Liveness Detection Using a sequential CNN technique [21]	CNN	CelebA-Spoof (2020) was collected to recognize live and non-live faces.	accuracy of testing the system on unseen data is 87% and the area under the ROC curve is 0.535	It got 87% of accuracy	Lack in capsule neural networks	there are many new techniques are intended to be used in future work such as capsule neural networks are expected to improve.
Face Detection System for Health Care Units Using Raspberry PI [22]	OpenCV NumPy SQLite Raspberry Pi Python	Uses personal component analysis (PCA) in face recognition. Open-source libraries of python are used to process the image recognition algorithm. SQLite is used to store the data of the desired people.	the system is fast enough to complete the whole recognition process minimum three times in a second	The system is very helpful and efficient because there is no background effect for recognizing the person. It can recognize a person even though the environment and background changes. And it works satisfactorily in different lighting conditions.	slow image recognition algorithm fails to identify a moving person	Improve in the effect on the recognition process and slow image recognition

Developing a Multi-factor Authentication-based Cardless Electronic Payment System [23]	Authentication ICT NFC NEFT NIP ATM POS MMO		developed an electronic payment system that combines all the bank accounts of a particular holder together and access granted to them with or without a payment card	Reduced the cost of producing cards as well as the risk of carrying them all around.	the feature is not currently active nor utilized to fully ensure security measures to eliminate deceitful acts	Work more on the security side since it's the first initial part of the whole system
IoT based smart security and surveillance system [24]	Raspberry Pi OpenCV Python		Tested fully and successfully developed a system to demonstrate its feasibility and effectiveness.	The result of the testing illustrates that the monitoring system works well.	There is the unavailability of wireless relay connection also wireless sensor	system can be extended further by adding infrared emitting system to detect the person's face if they wore the mask on his/her face.
Pass Face Enabling Practical Anti-Spoofing Facial Recognition with Camera Fingerprinting [25]	-estimate Photo Response Non-Uniformity (PRNU), which is a unique and physically irreproducible camera fingerprint, to authenticate a smartphone with the capability of defeating impersonation attacks. Moreover, the estimated PRNU is extracted merely from raw videos used for face recognition, releasing the requirements of additional operations and compatible with most commercial off-the-shelf smartphones.	-The PCE values between fingerprints from the same device are collected as positive samples, and the PCE values between fingerprints from different devices are negative samples	-evaluate the accuracy of the authentication protocol using TAR, FAR, EER, AUC, and CDF.	-propose an anti-spoofing facial recognition system, PassFace, which integrates camera fingerprinting to defeat impersonation attacks for facial recognition authentication. The system is attack-resilient, user-friendly, and highly compatible with	-photo-spoofing attack, video-replay attack, and 3D facial mask attack.	-propose an anti-spoofing facial recognition system, PassFace, which verifies a user's face and his/her smartphone used for authentication simultaneously.

				existing face recognition approaches.		
Multi-Factor based Face Validation Attendance System with Contactless Design in Training Event [26]	<ul style="list-style-type: none"> - using a CNN (Convolutional Neural Network) technique - using the technique of KNN (K-Nearest Neighbor) 	The enrolled image dataset of 130 participants utilizing the proposed system was used to create two identification models and the accuracy of the two models was tested with all the face images obtained from this project.	- questionnaire has discrepancies at a level of 0.1 (or confidence level was 90.2%) based on the formula of Taro Yamane (1973). Ease-of-use is the priority in a time attendance system. User accuracy and user transparency were ranked second and third	<ul style="list-style-type: none"> - the proposed two-factor scheme is more effective and did not incorrectly identify any users. - implementation of a face time attendance system with an additional factor, a QR code to improve accuracy 	- using only one biometric factor such as facial data may limit accuracy and use, and is not practical in a real environment	-the system should be user-friendly by reducing processing time and being highly accurate and durable against fraud. The comparison of the two authentication method using a QR code and face verification with other methods
-eKYC (Electronic Know Your Customer) system [27]	-The face recognition and anti-spoofing detection module for an eKYC system was implemented using the Local Binary Pattern Histogram facial recognition algorithm coupled with a designed convolution neural network-based architecture to provide robustness to the system against most common	-system has been manually created with over 1000 images, 125 face images of each a person with 100X100 resolution of each image.	- The advancement in the performance of CNN based techniques in the Computer Vision and Pattern Recognition tasks, CNN approaches are robust and proved to have yielded better results in Anti-Spoofing systems.	-the live feed of a person was recorded, and the face is recognized successfully with the confidence value recorded on the extreme right corner.	-Face recognition system is very prone to spoofing Attacks. -the advancements in technology and easy wearable devices the spoofers can get easily habituated to gain unauthorized access to the system by disguising	-Anti-spoofing systems have been developed based upon various existing models and algorithms namely Convolution Neural Networks (CNN) which is an excellent Deep learning-based

	spoofing ways.				as a registered user.	architecture
<p>-CNN BASED MASK DETECTION SYSTEM</p> <p>Which is a Safety system for mask detection during this COVID-19 pandemic [28]</p>	<p>- OPENCV AND MOBILENETV2</p>	<p>- Kaggle's Medical Mask Dataset by Mikolaj Witkowski which contains images of many people wearing masks and XML files that contain the descriptions.</p> <p>- artificially generated mask dataset developed by Prajna Bhandary available at PyImageSearch which contains standard face images with applied facial landmarks.</p>	<p>- without mask: precision 1.00 // recall 0.99 // F1-score 0.99</p> <p>-with mask: precision 0.99// recall 1.00 // F1-score 0.99</p>	<p>- The proposed model for the detection of face masks is successfully done with the model created with CNN architecture using MobileNetV2 which gave a good result with perfect accuracy of detection.</p>	<p>-problems involved in face mask recognition for face authentication and face matching on a masked face,</p>	<p>- a deep learning-based feature is proposed</p>
<p>RFace: Anti-Spoofing Facial Authentication Using COTS RFID [29]</p>	<p>- RFace only requires users to pose their faces in front of a tag array for a few seconds, without leaking their visual facial information</p>	<p>- invite 30 volunteers (10 females and 20 males) aged from 18 to 30 to participate in our experiments. In the registration</p>	<p>- define six metrics to evaluate RFace: Authentication Success Rate (ASR), False Accept Rate (FAR), False Reject Rate (FRR), Receiver Operating Characteristic</p>	<p>- novel facial authentication system named RFace with COTS RFID devices. RFace ensures</p>	<p>- suffering from privacy leakage and spoofing attacks</p>	<p>- novel privacy-preserving anti-spoofing FA system, named RFace, which extracts both the 3D</p>

		<p>n phase, we collect three groups of RF signals (each group contains 60 fusion feature blocks). For each legitimate user, each attempt to authenticate takes about 225 seconds.</p>	<p>(ROC), Equal Error Rate (EER) and Defense Success Rate (DSR).</p>	<p>privacy-preserving and spoofing-resistant simultaneously.</p>		<p>geometry and inner biomaterial features of faces using a COTS RFID tag array.</p>
<p>Securing facial recognition: the new spoofs and solutions [30]</p>	<p>-eye tracking -natural micro-motion detection -depth detection</p>	<p>-ISO 30107 outlines three proposed levels for spoofs that can be summarised as Level A – pictures; Level B – video replay and paper masks; Level C – 3D masks¹. To help guide users, the US National Institute of Standards and Technology (NIST) has developed a series of standards for facial spoof presentation</p>	<p>-In this experiment, we mainly focus on the time cost of the fingerprint verification procedures. Table II lists the average time cost (100 runs) for each procedure. Because our system sequentially handles every key frame, TPRNU increases linearly with the number of keyframes. This can be reduced by handling multiple frames in parallel.</p>	<p>- follow general security best practices to mitigate attacks-enforce a progressive ‘failure back-off</p>	<p>- hackers use AI techniques and image editing tools to imitate the facial identity of the target user. Hackers use AI techniques and image editing tools to imitate the facial identity of the target user.</p>	<p>- robustly detect the fundamental attack vectors – picture and video spoofs</p>

AI-based content filtering system using an age prediction algorithm. [31]	Age estimation. Face recognition. CNN.	uses deep Convolution Neural Network (CNN) pre-trained based on the VGGFace and fine-tuned on the age dataset to extract the predicted age distribution also Pre-training of CNN is done by ancillary dataset for updated weights.	Improvement in performance of age estimation with RoR models.	For age estimation Guided CNN(AE-CNN) there are promising results on two well-known public domains.	Ordinal regression problems can be solved by using CNN.	Designing a face recognition and age prediction model in the future helps to prevent fraud and scams, where the proposed combined model for face recognition and age prediction can be effective.
Deep Residual Learning for Facial Emotion Recognition. [32]	Fold validation techniques. ResNet50 model.	The datasets that were used in this research are CK+ and Kaggle FER.	Using the two datasets and accuracy was validated using a confusion matrix and 5-fold validation techniques.	Hyperparameters (Learning Rate, Epoch, Batch size, and dropout) were varied in the work. The learning rate was varied from 0.1 to 0.0001 and the best result was obtained in 0.001.	With the increase of the network depth there exist a degradation problem associated with it.	With the increase of depth and using identity shortcuts, better feature learning can be achieved ultimately delivering a high-performing network.
Face Recognition in the Context of Website Authentication. [33]	InceptionV3 algorithm. Machine learning algorithms. Support vector machines (SVM).	Includes 13,668 pictures of 1409 persons, that are collected from internet resources	It was found that logistic regression performs better than traditional machine learning algorithms. The reported results are significant	Deep learning-based techniques for face recognition over a collected	Issues associated with big data in cloud computing.	Diversified and enhanced in-house dataset by inviting more volunteers and investigati

		and some volunteer's images with links.	in face recognition-based web authentication.	dataset are superior to conventional machine learning techniques.		ng new deep learning architectures while tuning hyperparameters.
Biometric applications in education. [34]	Image processing techniques. Recognition technique. Biometric technique.	Biometrics can improve essential aspects such as a patient's identity and support with real-time information to offer adequate medical services.	Biometric technologies are disrupting several industries and sectors. General applications include its use for recreational activities and It can also be used for replacing password systems.	Early results are very promising and practical ; however, more experiments and validations are required to have overall effects in other knowledge and educational settings.	As biometrics is relatively new, users might be reluctant to use it. It could pose various problems such as wide variance when measuring characteristics, affecting the system's performance.	For this technology to advance, it is necessary to educate future engineers in this technology well. The future seems promising for biometric technology ; the biometric technology market is expected to reach a value of USD 94 billion by 2025 at a compound annual growth rate of 36%.
AI-based content filtering system using an age prediction algorithm. [35]	Age estimation. Face recognition. CNN.	uses deep Convolution Neural Network (CNN) pre-trained based on the VGGFace and fine-tuned on the age dataset to extract the predicted age distribution	Improvement in performance of age estimation with RoR models.	For age estimation Guided CNN(AE-CNN) there are promising results on two well-known public domains.	Ordinal regression problems can be solved by using CNN.	Designing a face recognition and age prediction model in the future helps to prevent fraud and scams, where the proposed combined model for face recognition

		n also Pre-training of CNN is done by ancillary dataset for updated weights.				n and age prediction can be effective.
biometric facial recognition on an Android operating system intended for authentication [36]	machine-learning techniques	biometric data can relate someone to its former activities or monitor their actual, present operations and can be an impressive resource for data mining	the built-in camera can be used for biometric face authentication, implemented with little computation overhead rather than expensive or large hardware.	the detection is not possible, but the device is permanently trying to get a proper image so that it can perform the analysis. Neither is authentication possible if the user is wearing a mask or any other gadget, piece of clothing, etc. which covers the face	doesn't do the recognition	The algorithm could be improved regarding the performance by using machine learning techniques
Secure and Usable User Authentication via Earphone IMU [37]	The authentication merely requires the user to voice a short 'EMM' for generating the vibration	IMU data contains too much noise, constraining the distinguishability of collected biometric.	biometric extractor by comparing the classification accuracy of different classifiers, i.e., SVM, NB, DT, KNN, NN, and biometric extractor (BE).	realized MandiPass with off-the-shelf devices and conducted extensive experiments to evaluate its performance in	echo does not have the ability	The security of MandiPass is further enhanced via cancellable templates and transformation countermeasures.

				real-world environments.		
Face Recognition Using Popular Deep Net Architectures [38]	CNN.	The datasets that were used in this research are CK+ and Kaggle FER.	ImageNet dataset. - BSL signs were recorded using a portable Continuous Waveform (CW) radar with a carrier frequency equal to 24GHz.	Evaluate the classification, when comparing the relative performance of different classifiers with their values for precision and recall, the need for a single metric appears.	with Graphics Processing Units (GPUs), as well as increasing overall accuracy and performance. The model accomplishes this by making use of Rectified Linear Units (ReLU), as	we need to evaluate our image classification methods not only with accuracy metrics and classification reports but also concerning how much memory each model uses, as well as how much processing time it takes for that model to classify the images.
Your Eyes Show What Your Eyes See [39]	PA Detection (PAD) method named "Your Eyes Show What Your Eyes See (Y-EYES) ML	two ML datasets, including facial data for identity verification and corneal reflection data for learning liveness authentication.	Y-EYES is effective and efficient in detecting the liveness against sophisticated PAs	The experimental results in accuracy and performance show that Y-EYES is effective and efficient in detecting the liveness against sophisticated PAs	does not require any expensive extra sensors.	- robustly detect the fundamental attack vectors – picture and video spoofs

Approach for Face Detection using Max Pooling [40]	OpenCV NumPY SQLite Raspberry Pi Python	Open source libraries of python are used to process the image recognition algorithm. SQLite is used to store data of the desired people.	system is fast enough to complete the whole recognition process minimum three times in a second	The system is very helpful and efficient because there is no background effect for recognizing the person	slow image recognition algorithm fails to identify a moving person	Improve in the effect on the recognition process and in slow image recognition
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Most of the application uses a Convolutional neural network (CNN) which is a neural network that has one or more convolutional layers and is used mainly for image processing, classification, segmentation, and other auto correlated data. Face recognition is the technique of recognizing a person by comparing some attributes of a new person (input sample) with those of previously identified people in a database. Face recognition is divided into four stages: face region detection, alignment, feature extraction, and classification [21], with feature extraction being the most important. For limited situations, handcrafted features have shown to be effective [22-24]. However, in the setting of real-world challenges such as shifting positions, attitudes, lighting, and picture quality, the recognition of unconstrained face photos is an emerging and complex topic [34].

CHAPTER – II

MATERIAL AND METHODS

This section of the report explains the meaning of face and gesture recognition, how it was implemented in the system, and the tools that were utilized to make it work.

3.1 FACIAL RECOGNITION

Facial recognition is a method of recognizing or verifying a person's identification by looking at their face. People can be identified in pictures, films, or in real time using facial recognition technology. Face recognition software use computer algorithms to identify specific, distinguishing features on a person's face. These features, such as eye distance or chin shape, are then transformed into a mathematical representation and compared to data from other faces in a face recognition database.

When producing identification documents, facial recognition is frequently integrated with other biometric technology such as fingerprints (preventing ID fraud and identity theft).

The technology is used for a variety of purposes. These include law enforcement, airports, and border control where facial recognition has become a familiar sight at many airports around the world. Increasing numbers of travellers hold biometric passports, which allow them to skip the ordinarily long lines and instead walk through an automated ePassport control to reach the gate faster. Facial recognition not only reduces waiting times but also allows airports to improve security.

The system will be using face recognition to provide authentication, so once the user is verified, he is provided access to his account. At all points of user interaction with the App, the user face will be monitored to make sure that the user is still around. The session details and the user's face will be monitored constantly to avoid any case of an authenticated user moving from the chair and an intruder trying to access the account.

3.2 GESTURE RECOGNITION

Gesture recognition is a computing process that attempts to recognize and interpret human gestures using mathematical algorithms. Gesture recognition is not limited to just human hand gestures but rather can be used to recognize everything from head nods to different walking styles.

Gesture recognition technology that is vision-based uses a camera and motion sensor to track user movements and translate them in real-time. Newer cameras and programs allow for the tracking of depth data as well, which can help improve gesture tracking. Using real-time image processing, users can interact with the program immediately to achieve the desired results.

Gesture recognition can be used to improve a variety of fields, such as security where programs can be set up to recognize hand gestures and to send alerts in response, and in public health by removing the need for touchscreens on self-service kiosks, businesses and organizations could help reduce the number of germs being spread. This is especially helpful for mitigating the spread of infectious diseases such as Covid-19.

The system will be using gesture recognition to provide authorization, as we plan to develop gesture-based clearance systems that are in line with the terminology used by the USA Department of Défense. Different hand gestures made by an authenticated system will take as different commands to switch the mode and let the user access his data objects whose sensitivity is lesser than the user mode. This can be helpful wherein the user must switch roles quickly on seeing someone approaching his desktop personally.

3.3 IMPLEMENTATION TOOLS

- a. Python is a computer programming language often used to build websites and software, automate tasks, and conduct data analysis. Python can be used to create a variety of different programs and isn't specialized for any specific problems.
- b. IDE: stands for the integrated development environment, it is software for building applications that combines common developer tools into a single graphical user interface (GUI).
- c. Visual Studio: is a streamlined code editor with support for development operations like debugging, task running, and version control. It aims to provide just the tools a developer needs for a quick code-build-debug cycle and leaves more complex workflows to fuller featured IDEs, such as Visual Studio IDE.
- d.byCharm: PyCharm is a Python Integrated Development Environment (IDE) that includes a variety of key tools for Python developers that are tightly integrated to create a pleasant environment for effective Python, web, and data science development.

3.4 PACKAGES

- I. OpenCV: is a fantastic program for image processing and computer vision tasks. It's an open-source library for tasks including face detection, objection tracking, landmark detection, and more. Python, Java, and C+ are among the languages supported.
- II. SQL-Lite: is a programming language that is used to create embedded software for devices such as televisions, cell phones, cameras, and other electronic gadgets. It can handle HTTP requests with low to medium traffic.
- III. Tkinter: is the authentic way in Python to create Graphical User interfaces (GUIs) and is included in all standard Python Distributions. It's the only framework built into the Python standard library.
- IV. Facial recognition: it is the latest trend in Machine Learning techniques. OpenCV, the most popular library for computer vision, provides bindings for Python. OpenCV uses machine learning algorithms to search for faces within a picture.

- V. Cvlib: is a easy, easy-to-use, high-level (you don't have to worry about what's underlying) open-source Computer Vision library for Python that is used to construct inserted software. The library was created with the goal of making experimenting simple and quick.
- VI. MediaPipe: is a Google cross-platform library that provides amazing ready-to-use machine learning solutions for computer vision tasks. The Python OpenCV library is a computer vision toolkit that is widely used for image analysis, processing, detection, and identification.
- VII. Tensorflow: Google designed and distributed a Python library for fast numerical computing. It is a foundation library that can be used to develop Deep Learning models directly or via wrapper libraries built on top of TensorFlow to make the process easier.
- VIII. Numpy: is a Python library for manipulating arrays. It also provides functions for working with matrices, fourier transforms, and linear algebra.
- IX. Sqlite3: is a C library that offers a lightweight disk-based database that doesn't require a separate server process and may be accessed with a nonstandard SQL query language.
- X. PIL image: The Python Imaging Library (PIL) extends the Python interpreter's image processing capabilities. This library supports a wide range of file formats, has a fast internal representation, and can perform some image processing.
- XI. PIL ImageDraw : Image objects benefit from simple 2D visuals. This module is used to create new photos, annotate, or retouch old images, and create graphics for use on the web on the fly.

CHAPTER - III
SPECIFICATION AND DESIGN

This section of the report explains the meaning of face and gesture recognition and how it works using programming.

4.1 FACIAL RECOGNITION

Facial recognition is a technology-based method of recognizing a human face. Biometrics are used in a facial recognition system to map facial traits from a photo or video.

What exactly is facial recognition and how does it work? The following are the main steps, which vary depending on the technology:

Step 1: A photo or video is used to obtain an image of your face. It's possible that your face will appear alone or in a throng. You may appear to be looking straight ahead or virtually in profile in your photograph.

Step 2: The geometry of your face is scanned by facial recognition software. The distance between your eyes and the distance from your forehead to your chin are important considerations. The software recognizes facial landmarks (one system recognizes 68 of them) that are important in differentiating your face.

Step 3: A database of known faces is matched to your facial signature, which is a mathematical formula.

Step 4: A decision is reached. Your faceprint might match one in a database of facial recognition images.

4.1.1 PROGRAMMING

```
path = "C:\\Users\\user\\Desktop\\FRS\\testing"
myList = os.listdir(path)
encodeList=[]
student_names=[]
for img in myList:
    curImg = face_recognition.load_image_file(f'{path}/{img}')
    img_encoding = face_recognition.face_encodings(curImg)[0]
    encodeList.append(img_encoding)
    student_names.append(os.path.splitext(img)[0])
known_face_encodings = encodeList
known_face_names = student_names

cap = cv2.VideoCapture(0)
namez = []

success, test_image = cap.read()
face_locations = face_recognition.face_locations(test_image)
face_encodings = face_recognition.face_encodings(test_image,
face_locations)

pil_image = Image.fromarray(test_image)
draw = ImageDraw.Draw(pil_image)
name = "Unknown"
for (top, right, bottom, left), face_encoding in
zip(face_locations, face_encodings):
    matches = face_recognition.compare_faces(known_face_encodings,
face_encoding)

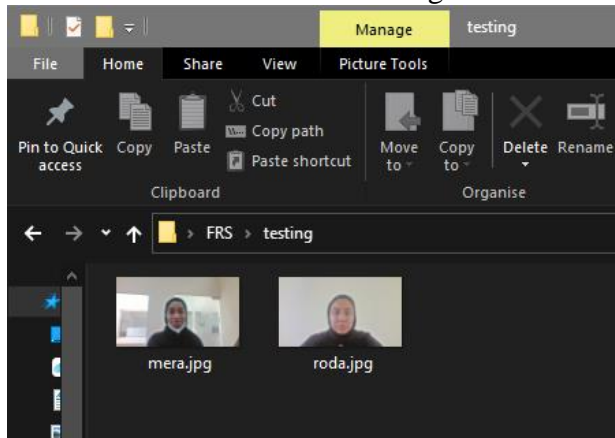
    if True in matches:
        first_match_index = matches.index(True)
        name = known_face_names[first_match_index]
        namez.append(name)
        draw.rectangle(((left, top), (right, bottom)), outline=(0,
0, 0))

        text_width, text_height = draw.textsize(name)
        draw.rectangle(((left, bottom - text_height), (right,
bottom)), fill=(0, 0, 0), outline=(0, 0, 0))
        draw.text((left + 6, bottom - text_height - 5), name, fill=(255,
255, 255))

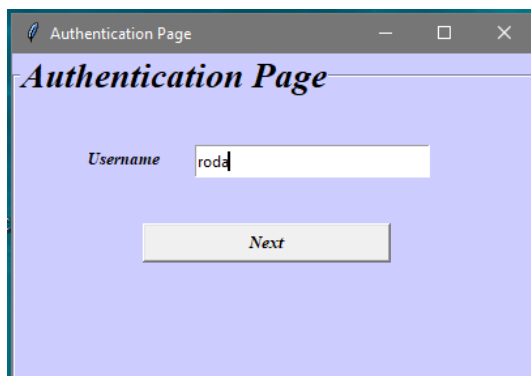
    print(name)
    if name!=username:
        print('Username and Image does not match')
        exit()
    del draw
```

4.1.2 SCREENS

Saved photos will be saved in this folder so that the code can compare the picture, the entered username and the live facial recognition are all the same person.



Enter the username (make sure that the username is same as the name of the picture saved in the folder).



After successful access it will show the user's profile.



4.2 GESTURE RECOGNITION

A gesture recognition system begins by taking frame-by-frame photos of hand placements and gestures with a camera focused on a specific three-dimensional zone within the vehicle. This camera is usually positioned on the roof module or another unobstructed observation point. Even when there isn't much natural light, the system illuminates the region using infrared LEDs or lasers to provide a crisp image.

These photos are evaluated in real time by computer vision and machine learning technologies, which use a prepared library of signs to interpret the hand motions into commands.

4.2.1 PROGRAMMING

```
from handDetector import HandDetector
import cv2
import math
import numpy as np
from PIL import ImageColor

handDetector = HandDetector(min_detection_confidence=0.7)
webcamFeed = cv2.VideoCapture(0)

while True:
    status, image = webcamFeed.read()
    handLandmarks = handDetector.findHandLandMarks(image=image, draw=True)
    count = 0
    img = ImageColor.getrgb("blue")
    if (len(handLandmarks) != 0):
        # we will get y coordinate of finger-tip and check if it lies above
        # middle landmark of that finger
        # details: https://google.github.io/mediapipe/solutions/hands

        if handLandmarks[4][3] == "Right" and handLandmarks[4][1] >
handLandmarks[3][1]: # Right Thumb
            count = count + 1
            img = ImageColor.getrgb("red")

        elif handLandmarks[4][3] == "Left" and handLandmarks[4][1] <
handLandmarks[3][1]: # Left Thumb
            count = count + 1
            img = ImageColor.getrgb("green")

        if handLandmarks[8][2] < handLandmarks[6][2]: # Index finger
            count = count + 1
            img = ImageColor.getrgb("blue")
```

```

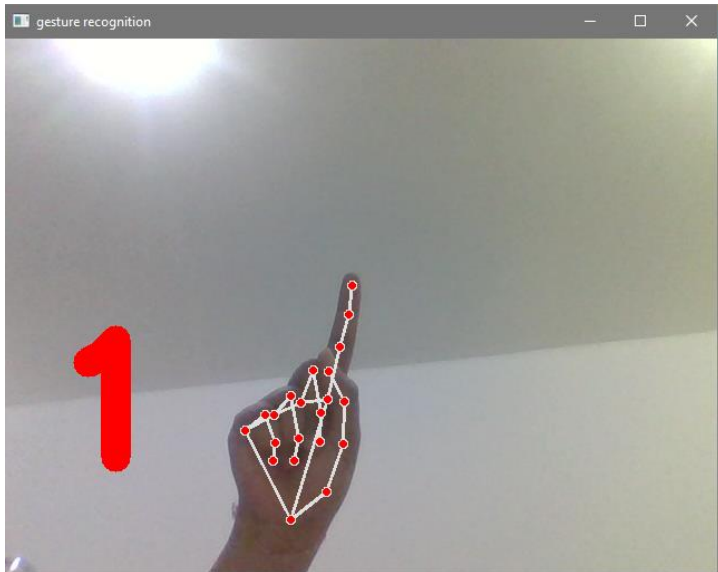
    if handLandmarks[12][2] < handLandmarks[10][2]: # Middle finger
        count = count + 1
        img = ImageColor.getrgb("red")
    if handLandmarks[16][2] < handLandmarks[14][2]: # Ring finger
        count = count + 1
        img = ImageColor.getrgb("green")
    if handLandmarks[20][2] < handLandmarks[18][2]: # Little finger
        count = count + 1
        img = ImageColor.getrgb("blue")

    cv2.putText(image, str(count), (45, 375), cv2.FONT_HERSHEY_SIMPLEX, 5,
img, 25)
    cv2.imshow("Volume", image)
    cv2.waitKey(1)

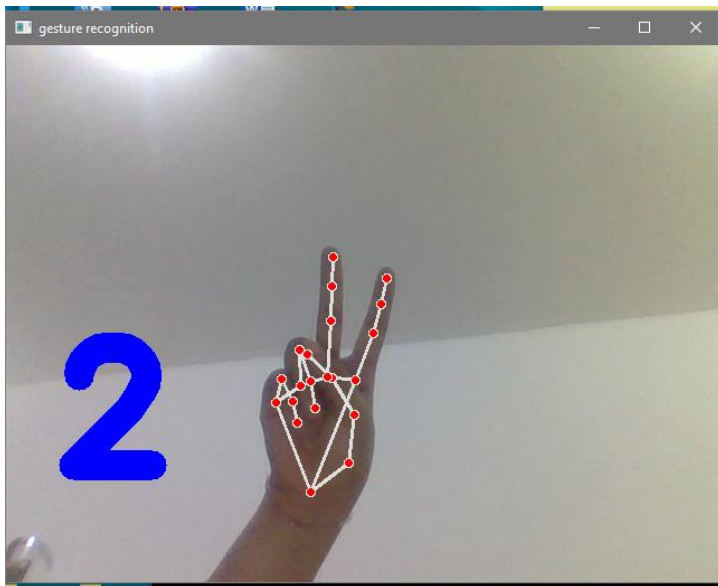
```


4.2.2 SCREENS

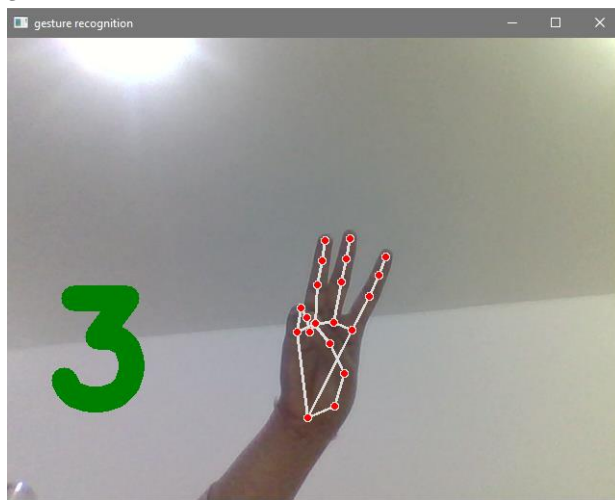
1



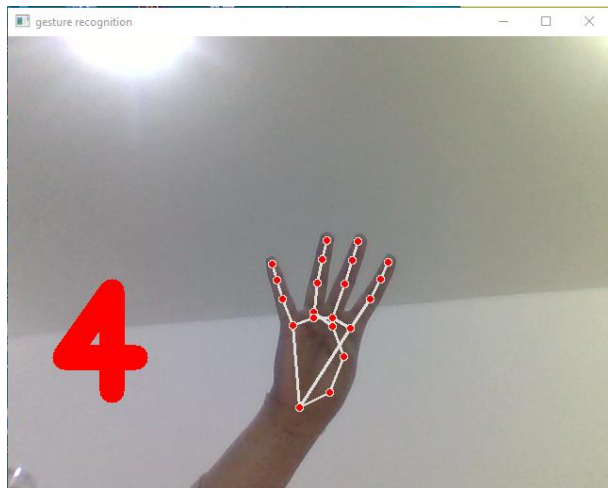
2



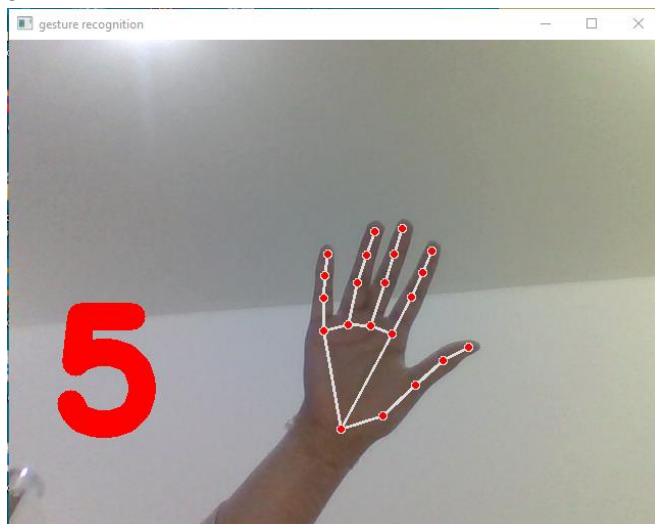
3



4



5



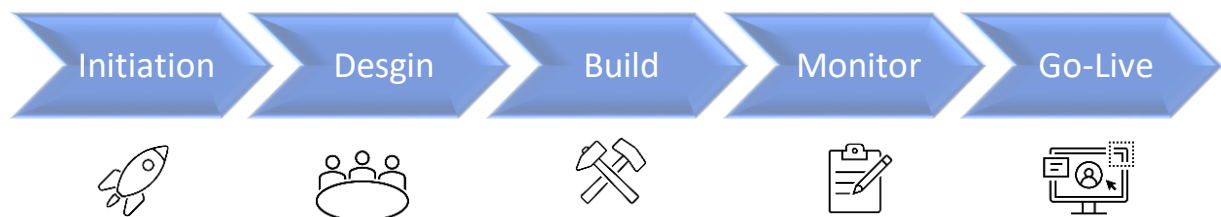
CHAPTER - IV

IMPLEMENTAION METHOLODOGY

This chapter explains how projects are implemented in the field and demonstrates the nature of the proposed system.

5. IMPLEMENTATION METHODOLOGY

The implementation methodology can be split into five stages. First, initiate the project, and then Design it. Next, we build the project and monitor its performance. Finally, once the project is completed, it must be closed out.



1. Initiation:

The first thing we did was come up with a concept to transform into a reality, hence, we figured, why not build an application that can give us with excellent data or information security while also cooperating with the two approaches to human authentication: something you know, like passwords, and something you are, like your face. We've decided to call it towards information protection using facial and gesture recognition. We started this part in the previous semester by conducting a literature review for both facial and gesture recognition to help us prepare and learn about them since we are not programmers.

We set our goals for this project after reading several publications concerning facial and gesture recognition, one of which was security, for which we used two-factor authentication (2FA). Biometric authentication has become part of the procedure. Facial recognition software analyses an employee's face and converts the data into a mathematical formula. It is then compared to a database to ensure that the face matches the name, all in a matter of seconds.

2. Design:

We wanted a basic and easy-to-use application that was also simple to design, the list below illustrates multiple implementation tools:

- Python: Python is a free and open-source programming language used in web development, data analysis, artificial intelligence, and a variety of scientific applications.
- SQLite: SQLite is a software library that creates a transactional SQL database engine that is self-contained, serverless, and requires no configuration.
- Visual Studio: is a simplified code editor that includes features for debugging, task execution, and version management.

We also used a number of packages to help the application, such as OpenCV, Tkinter, PIL Image. facial recognition, etc. And the structure of the application that we've constructed is visualized in Figure 10, as it will help give us guidance and follow each process one by one easily.

3. Build:

The concept has been defined, the tools and packages have been prepared, and it is now time to begin developing the application. All of the windows will have the same concept, colour, font and frame. The first stage is to design the application's home page. The front page is demonstrated in Figure 1.

If the user has not yet registered, he or she should do so by clicking the register button, which will take the user to the registration page. Full name, user id, date of birth, gender, nationality, residence, and phone number are all listed on the website. Following figure 2 illustrates this.

If the user is already logged in, he or she should click the login button, which will take them to the authentication screen shown in Figure 3. The screen will just ask for your username, so when you click the next button, the camera will open and compare your face to the saved photo, granting you access to your profile if your photo is in the folder in figure 4.

Following your gain of access, you will be presented with a number of options, as shown in Figure 5. The first option we added is the add secret button, which allows you to create more secrets. The secret creation page in figure 6 has the date, which cannot be changed because it prints on the same day as the new secret is generated. It also has a secret id, the secret itself, and a secret type, which specifies the level the secret is at, with 1 being the lowest and 5 being the highest.

By tapping the secret button on the welcome page figure 5, the user can view his secrets. When the user clicks on it, a secret list with the secret id, the secret, and the secret level appears, as illustrated in figure 9.

4. Monitor:

✓✓✓✓

Application Checklist

This checklist is updated weekly to keep track of what has been completed and what has not.

✓✓✓✓

TOWARDS INFORMATION PROTECTION USING FACIAL AND GESTURE RECOGNITION

☐ **Data mining & information retrieval**
Installing tools and packages such as [anaconda](#), SQL Lite , OpenCV and pandas for data analysis .

☐ **Risk assessment**
represents the overall process in which [it](#) identifies hazards and risk variables that have the potential to cause harm. Analyze and assess the risk that [is](#) [connected with](#) that hazard.

☐ **Literature review**
Implementing literature review for gesture recognition and facial [recognition](#).

☐ **Programming**
Explain facial and gesture recognition in further detail, as well as how it works with programming (python).

☐ **Methods and materials**
[Demonstrates](#) how it was implemented in the system, as well as the tools that were utilized to make it function

☐ **Devices**
Cell phone, charging cord, portable charger or battery pack, hand-orked radio, LED flashlight with extra batteries, and headlamp.

☐ **Methodology**
To gain a deeper understanding of the system's nature. For the suggested system, a methodology is developed.

☐ **Five implementation steps**
The team members should be able to understand and follow the five steps.

☐ **Project timeline**
Discusses the total projected costs of finishing a project within a given time span. It included a Gantt chart, which displays a detailed visual overview of a project from start to finish.

☐ **Clear and easy**
The overall program is straightforward and simple to use, as well as simple to build and create.

☐ **Testing**
Once the application is completed, test it to ensure that it is functioning properly.

5.1 RESEARCH DESIGN

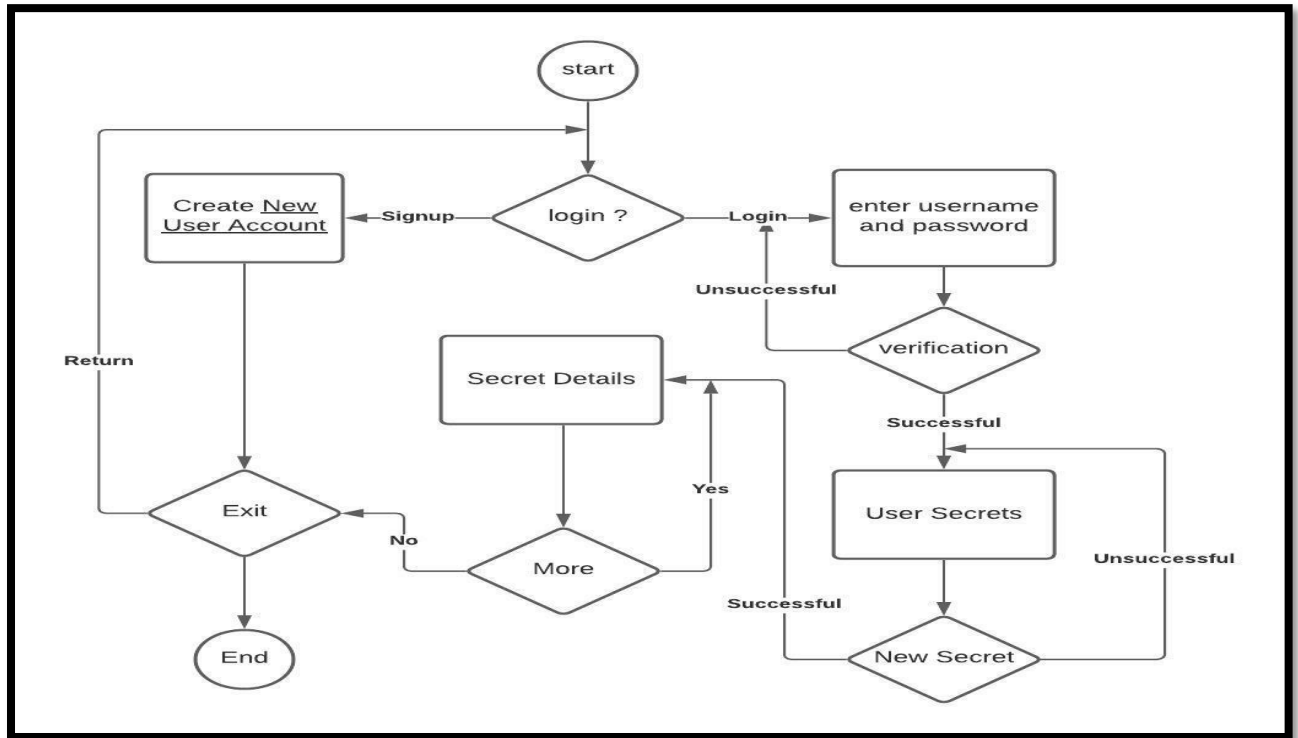


Figure 1

Figure 1 shows the flowchart of the proposed system that clarifies the steps that the user will take when the system begins to be used. The first step for this flowchart is that the system will ask the user if he has an account, if the user does not have an account, he can sign up by creating a new account, he enters his name, phone number, address, his id and its password, these details will be saved in both user registration form and login details. After creating the account, he can either exit or return to the login page and enter his username and password to access his files or page. it will verify by confirming in the login table. if the user enters the same username and password he can access the user secret, if it is different, then the system will redirect the user into the login page. After the successful login the user, the user can access his secrets, as well as creating one, to do that, the system will ask some of the inputs such as secret ID number, secret messages, and security clearance which means the security level of the message, this process is saved in a secret form. if you want to add more secret details you can return the secret details table and if not, you can exit the system.

Front page:

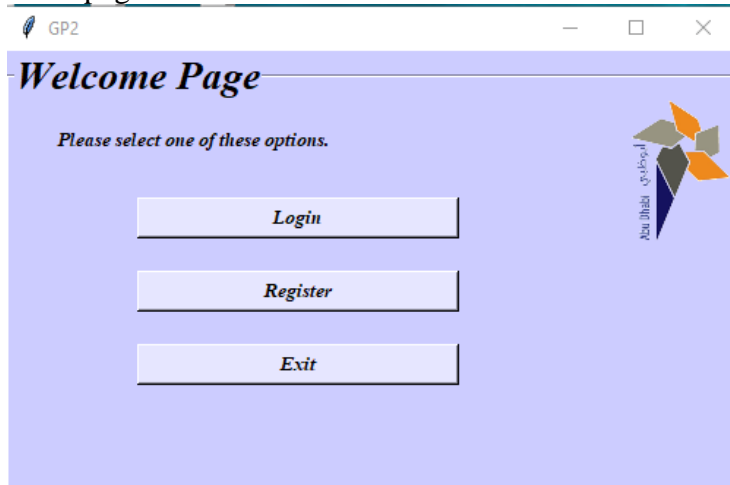


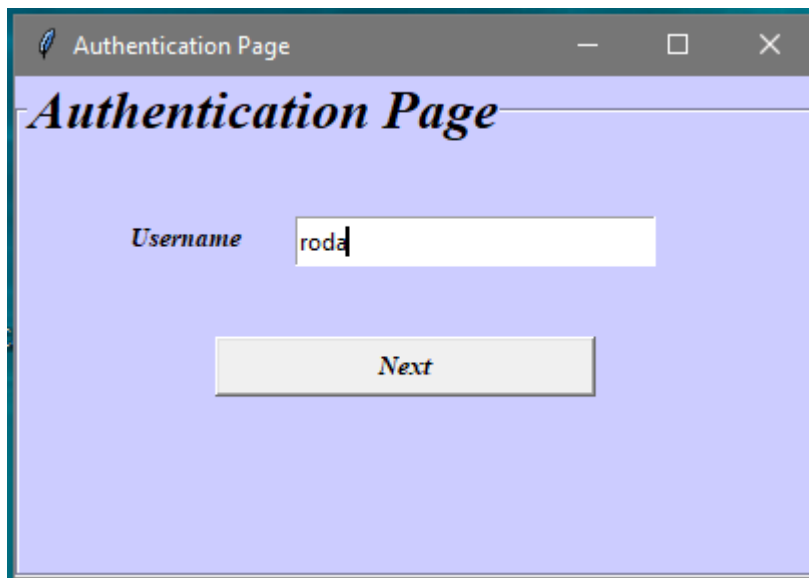
Figure 2. It shows welcome page which contains two web pages that appear the first time you open the system.

Register:

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
49	30	1	2	3	4	5	6
50	7	8	9	10	11	12	13
51	14	15	16	17	18	19	20
52	21	22	23	24	25	26	27
1	28	29	30	31	1	2	3
2	4	5	6	7	8	9	10

The Registration Screen for login details that require a user to enter verification certificates to access to the confidential form, it shows the form which the user can register, that's shown in Figure 3. It consists of full name, user id, DOB, contact number, nationality, gender, and residence, after filling everything, click register.

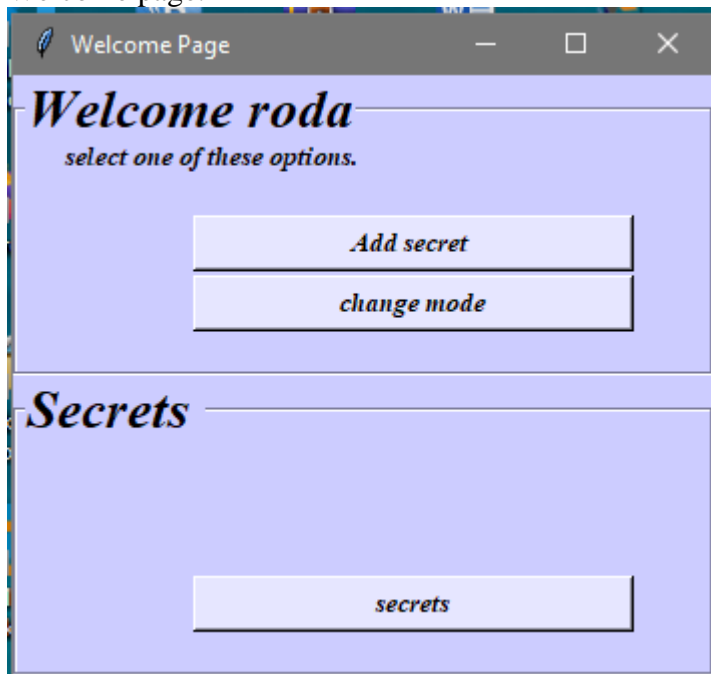
Login:



The screenshot shows a web browser window titled "Authentication Page". The page has a light blue background. At the top, the title "Authentication Page" is displayed in a large, bold, black serif font. Below the title, there is a label "Username" in a smaller, bold, black serif font. To the right of the label is a white text input field containing the text "roda". Below the input field is a light gray button with the text "Next" in a bold, black serif font.

Once the user is done filling the boxes, then he can submit, the information will be saved in the database and the user can log in as shown in Figure 4. Login Screens

Welcome page:



The screenshot shows a web browser window titled "Welcome Page". The page has a light blue background. At the top, the title "Welcome roda" is displayed in a large, bold, black serif font. Below the title, the text "select one of these options." is displayed in a smaller, italicized, black serif font. Below this text are two light gray buttons stacked vertically. The top button has the text "Add secret" in a bold, black serif font. The bottom button has the text "change mode" in a bold, black serif font. Below these buttons is a section titled "Secrets" in a large, bold, black serif font. Below the "Secrets" title is a light gray button with the text "secrets" in a bold, black serif font.

After he / she login into her/his account, it will shows two button one for "add secret" and another for "change mood". As shown in Figure 5.

Add secret:

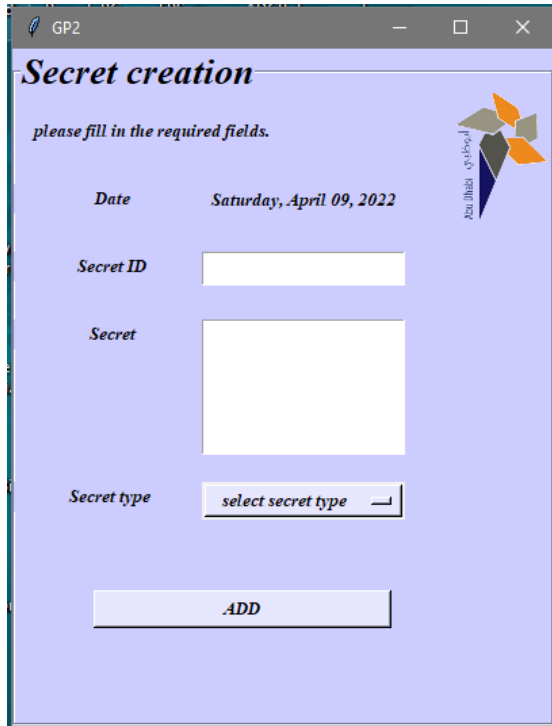


Figure 6. Once the user clicks on “Add secret”, the Secret creation page will show. The user needs to add Secret ID, Secret and Select secret type to create a secret.

Change mood

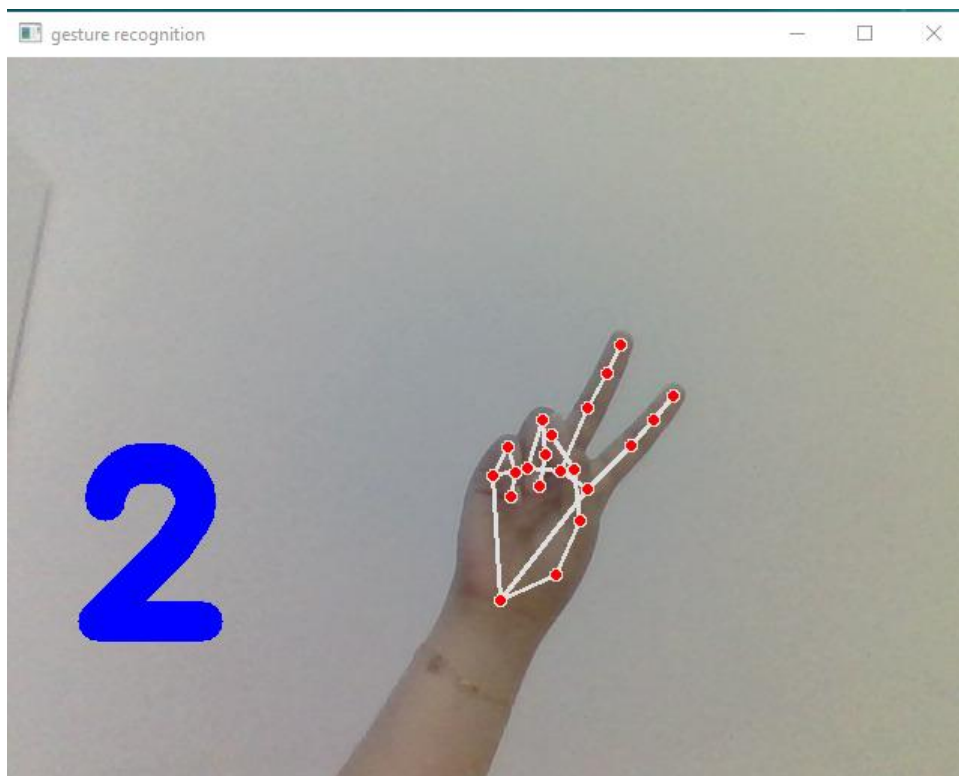


Figure 7.

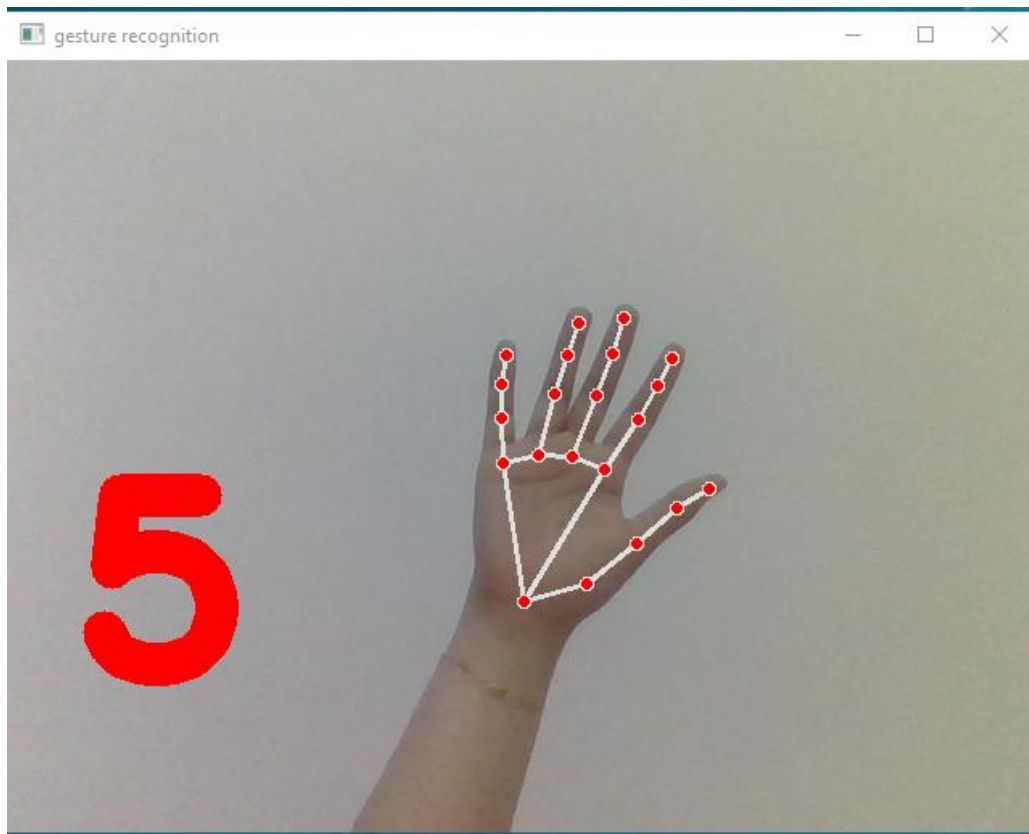


Figure 8

Secrets:

secrets				
<i>RH1</i>	<i>002</i>	<i>Personal Info</i>	<i>5</i>	<i>2/2/22</i>
<i>MZ1</i>	<i>001</i>	<i>Company Info</i>	<i>3</i>	<i>4/4/22</i>

Figure 9. Shows the list of secrets that was created.

Registration table:

The screenshot shows the DB Browser for SQLite interface. The title bar indicates the file path: C:\Users\user\Desktop\FRS\GP21.db. The menu bar includes File, Edit, View, Tools, and Help. The toolbar contains buttons for New Database, Open Database, Write Changes, Revert Changes, and Open Project. The main window has tabs for Database Structure, Browse Data, Edit Pragma, and Execute SQL. The 'Table:' dropdown is set to 'Table1'. The data table has 8 columns: Full Name, User Name, DoB, Gender, Nationality, Residence, and Phone No. It contains 5 rows of data.

	Full Name	User Name	DoB	Gender	Nationality	Residence	Phone No
	Filter	Filter	Filter	Filter	Filter	Filter	Filter
1	Roda Alhosani	RH1	8/12/98	Female	UAE	AbuDhabi	507777777
2	Maitha Alzahmi	MZ1	17/11/97	Female	UAE	AbuDhabi	509999999
3	Meirah Alyammahi	MR1	6/6/99	Female	UAE	Fujairah	505555555
4	Yasir Hamid	YH1	1/1/90	Male	UAE	Dubai	501111111
5	Lamya Albloushi	LH1	2/2/96	Female	UAE	Ras Alkhaimah	502222222

table 1.3

Secret table:

The screenshot shows the DB Browser for SQLite interface. The title bar indicates the file path: C:\Users\user\Desktop\FRS\GP21.db. The menu bar includes File, Edit, View, Tools, and Help. The toolbar contains buttons for New Database, Open Database, Write Changes, and Revert Changes. The main window has tabs for Database Structure, Browse Data, Edit Pragma, and Execute SQL. The 'Table:' dropdown is set to 'Table2'. The data table has 6 columns: User Name, Secret ID, Secret, Secret Level, and Date. It contains 2 rows of data.

	User Name	Secret ID	Secret	Secret Level	Date
	Filter	Filter	Filter	Filter	Filter
1	RH1	002	Personal Info	5	2/2/22
2	MZ1	001	Company Info	3	4/4/22

table 1.4

CHAPTER - V

RESULT AND EVALUATION

6. RESULTS AND EVALUATION

CHAPTER – VI
PROJECT FINANCIAL FEASIBILITY

This section of the report will assess the proposed project which is information protection using face and gesture recognition.

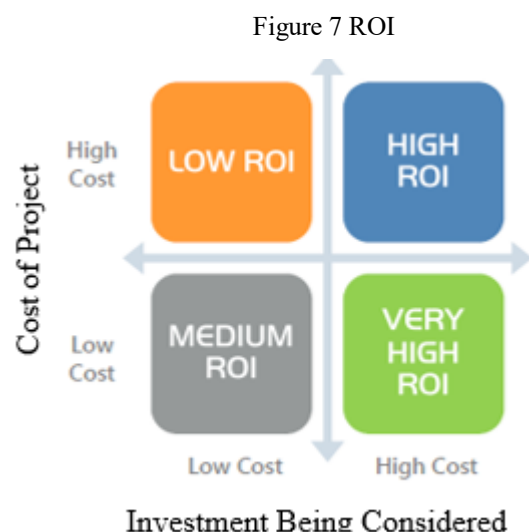
7. PROJECT FINANCIAL FEASIBILITY

A financial feasibility study projects how much start-up capital is needed, sources of capital, returns on investment, and other financial considerations. The study is an assessment of the financial aspects of something.

- **TCO (Total Cost of Ownership)** The initial investment in the project plus the operating costs. This metric aims at providing a holistic view of the total direct and indirect costs during the lifespan of the project. It is often calculated as the sum of Capital Expenditures (CapEx) and Operating Expenditures (OpEx).

- CapEx
 - Equipment such as cameras, computers, software
- OpEx
 - insurance, installation, training, future upgrades.

- **ROI (Return on Investment):** This metric shows the profitability of the investment in the project. It is estimated by dividing the net income by the initial costs.
- **Payback period:** Based on the projected income, how many months will be needed to recover the initial investment.



The estimation for the system annual cost around 15,000 DHS. 7000 DHS on the camera equipment's as it should be installed on the top of each screen in the organization, 4000 DHS on software, and the rest goes to the publication implying to publishing and promote the system to other organizations to use.

In the future, surely the system will get feedback and will be updated and developed to perform better. By adding more features to the system. the cost will get higher from our initial cost or price.

8. CONCLUSIONS

Face and gesture recognition may improve an organization's safety and security. It can also provide authentication and permission to secure your organization's information, which is one of the most sought-after fields in today's digital world.

To keep their users' trust, digital systems should have proper safety and security. We've created gesture-based clearance systems that follow the nomenclature used by the United States Department of Défense.

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