FUSION OF MULTIMODAL BIOMETRICS OF FINGERPRINT, IRIS AND HAND WRITTEN SIGNATURES TRAITS USING DEEP LEARNING TECHNIQUE.

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ABSTRACT: Due to expanding interest for the data security and safety guidelines everywhere, biometric authentication technology has been generally utilized in our regular day to day existence. With respects to this, multi-modal biometric innovation has acquired attention and became famous because of the capacity to a overcome the drawbacks of uni-model biometric frameworks. In Present research, novel multi biometrics recognition proof solution is developed, that depends to deep learning techniques for perceiving human utilizing multi biometric traits of Iris pattern, finger print data and offline signature biometrics. Framework of design depends on Deep Neural Networks (DNNs), for separating the parameters & classification of the image utilizing soft max based technique. To foster the framework, deep learning models are joined iris, finger print and off-line signature. To construct the VGG-19 network was utilized, and Adam streamlining technique has been applied for unmitigated to measure the degree of inequality was utilized as a misfortune work. A few strategies to stay away from overfitting were applied, like picture increase and drop-out procedures. For combining the deep learning networks, different combinations are utilized to investigate the impact of techniques on acknowledgment execution, accordingly component and score-level combination approach was applied. The exhibition of proposed framework is experimentally by directing a few trials to the SDUMLA-HMT data set, which is multi-modal biometric data set. Acquired outcomes showed that involving triple biometrics attributes in biometric distinguished proof frameworks got preferred outcomes over utilizing a couple biometric characteristics. The outcomes additionally shows that our methodology serenely beat other condition of- - the-craftsmanship techniques by accomplishing a precision of 99.11% on an element degree combination procedures and of 99.21 percent accuracy of various strategy for fusion at score level.

KEYWORDS : Deep Learning Technique, fusion, Iris , Fingerprint, machine learning, hand written signature.

I. INTRODUCTION

There is gain in momentum of the rise of present day mechanical assets as of late has led to a requirement for precise client acknowledgment frameworks to confine the employments of advancements. The biometric acknowledgment frameworks are the best impressive choice till date. Study of Biometrics is laying out the personality of an individual utilizing partial or completely mechanized procedures in light of social attributes, like voice or signature, or potentially actual characteristics, like iris trait and fingerprint data [1]. The novel idea of biometry information gives many benefits compared to conventional strategies, like secret word, as it can't be lost, taken, or duplicated [2]. Biometry characteristics can be arranged into twain gatherings: actual biometry, for example, iris and finger impression, social biometrics console composing and mark.

By and large, the biometric recognition solutions comprises of four major modules namely sensor module, extraction module, coordinating module and decision module [1]. There are two kinds of biometric acknowledgment frameworks, uni-model and multi-modal. The uni-model framework utilizes solitary biometrics attribute to perceive the client. As uni-model frameworks are reliable and have demonstrated better than recently utilized customary strategies, however they have impediments. These remember issue with commotion for the detected information, non-comprehensiveness issues, weakness to mocking assaults, intra class, and inter class similarities [4].

Essentially, multi modal biometry frameworks need multiple characteristic to perceive the subject [1]. It has been in general put in authentic application because of its effectiveness to address the issues experienced by uni-modal biometric solutions [4]. In multi biometric frameworks, various characteristics may be intertwined involving the accessible data in particular biometric framework module. There are many kinds of combination can implemented like at sensor level combination, attribute level combination, score level combination, & combination at decision level. The benefits of multi biometric frameworks over uni-modal frameworks has put together them an extremely appealing safe acknowledgment technique [1].

A few biometric analysts have depended on AI calculations for authentication purposes [9]. AI calculations need few derivation procedures to separate highlights in crude biometric information to change crude information into a suitable configuration prior to characterizing it. Hand Written Signature(HSW) recognition solution will generally check the personality of an individual in light of signature examination. Offline approach is for signatures written on sheet or captured by electronic gadgets. An electronic device called signature pad is used to capture offline signature in a LCD touchpad and pen type stylus. Off line signature identification, a combination of geometry, spatial and instance features utilised for the comparison processes [11].

Lately, significant learning had an amazing impact and made sublime results in biometric system [11-20]. The notable learning estimations has vanquished an extensive part of the constraints of AI computations, especially that are related to characteristic extraction algorithms. A notable take away estimations are adjust to biometric s picture changes and can remove features from rough data [21] . In perspective to remarkable execution of profound learning techniques in different acknowledgment errands, this study means to power research the utilization of the deep neural network calculation in perceiving an individual through triple biometric characteristics, namely iris, finger print and signatures. In research approach , an effective multi biometric identification solution is brought forward in view of constructing deep learning techniques related to iris, finger print and off line signature pertaining to an individual. Among these traits selected as finger print may be the most established generally broadly utilized and, subsequently, clear individual acknowledgment characteristics, while the exceptional and profoundly exact nature of acknowledgment data contained in the iris makes it a powerful choice. The third characteristic, off line signature, has been included respect to upgrading the exactness related to distinguishing proof outcomes and working on the safety and dependability of the solution proposed. Off line signature is a social bio metric characteristics, and not at all like other biometric is generally old and common acknowledged model of distinguishing proof and it is one of the moving errand to accomplish the improvement in ID of human framework. As of now, research on the combination of these three kinds of biometrics is still exceptionally restricted. Supposedly, no effort has been done on a multi biometrics recognizable proof biometric framework utilizing triple qualities, among them off line signature is one trait. Furthermore, the research investigates intertwining the qualities at two combination levels: fusion on feature level and score level combination utilizing two score techniques, in particular, math mean rule and the product rule. SDUMLA HMT, a freely accessible genuine multi biometrics dataset, utilized to framework assessment. The presented distinguishing proof framework bothers on start to finish CNNs models that concentrate elements and afterward group the individual without sending any picture division or identification strategies.

II. LITERATURE REVIEW

A couple of assessments have presented multi biometrics structures that take advantage of a combination of affirmation procedures It contains a scrutiny of progressing assessments which used standard AI and significant learning approaches in multi modal biometric structures.

Tracking down approaches to solidifying different physical biometric qualities has upheld a couple late biometric affirmation analysis. Bouzouina et al [5] presented a multi modal actually take a look at structure that merged facial biometric with iris characteristics to fusing at feature level. This assessment used several procedures for incorporate extraction and support vector machines applied estimation for client check and it conveyed a precision upto 98.6 percent. Hezil et al [6] presented structure of biometrics that used ear and palm-print ascribes followed by merging it at feature-level, It made surface descriptions and triple portrayal techniques. At other audit, Veluchamy et . al [7] applied weird genuine characteristics, fingervein, and knuclie qualities for make a multi modal biometric s ID system. The solution merged at characteristics feature fusion . Implementer used the K - SVM estimation and it structure acquired 98 percent accuracy.

Then again, a few investigations have zeroed in on perceiving the clients by conduct biometric attributes. In these frameworks, the component acknowledgment and extraction are troublesome since conduct qualities not offer dependability rehashed designs. Panasiuk et al. [11] talked the issue on fostering a framework utilizing k- nearest neighbor grouped which perceived client from blend of pad development and key stroke elements. This method formulated arrived at an exactness of 68.8 percent.

A review directed in AI-Waisey et al. [13] work presented a multi modal biometrics framework to client recognizable proof, named Iris Conv Net, that consolidate both the right as well as left eye iris utilizing positioning stage combination. Framework right off bat identified the iris pattern in the eye picture, afterward it recognized locale was gone into the neural network solution. Framework accomplished a 100 percent success case. Similar other review creators, work of AI- Waisy et al. [14] fostered biometry distinguishing proof framework in view of the facial image, and left eye and right eye iris pattern. Facial ID, one's face identification locale technique utilized, and afterward deep belief network (DBN) was put in. For image of iris distinguishing proof, Iris Conv Net [13] has been utilized. Different matching values merging strategies are utilized and good precision of presented framework was 99.9 percent.

In iris pattern the finest characteristics are assumed to set on random at the time of fetus growth of the human eye pattern It is also assumed to dissimilar among individuals and even in right and left image of the eye of the same individuals [7]. Few research in the field of deep learning are probably using hand written signature foe subject verification. For instance Kim et al. [18] develoved a multimodal biometric authentication solutions in view of CNN by intertwining mark and manually written letters in order.

In view of past examinations , this research creates as distinguishing proof multimodal framework that join fingerprint, iris , and signature utilizing the VGG-19 net. It is to choose the useful attributes that guide to out performs in previous solution, it is done first time. In order to take advantage of both two different techniques are used , additionally to improve types of choosing the major promising characteristics of the offline signature, and that give us apart from existing fusion solutions.

III. PROPOSED METHOD

In this research, we presented a DNN based multi biometrics framework utilizing fingerprint, human eye iris and off line signature attributes. Integrated design of the proposed strategy is shown in Fig 1. First and foremost, the fingerprint iris, and offline signatures of subjects are captured. At that point, the client personality is perceived by utilizing the multimodal framework, which is made out of three pre- implemented models for iris, fingerprints and offline signatures.

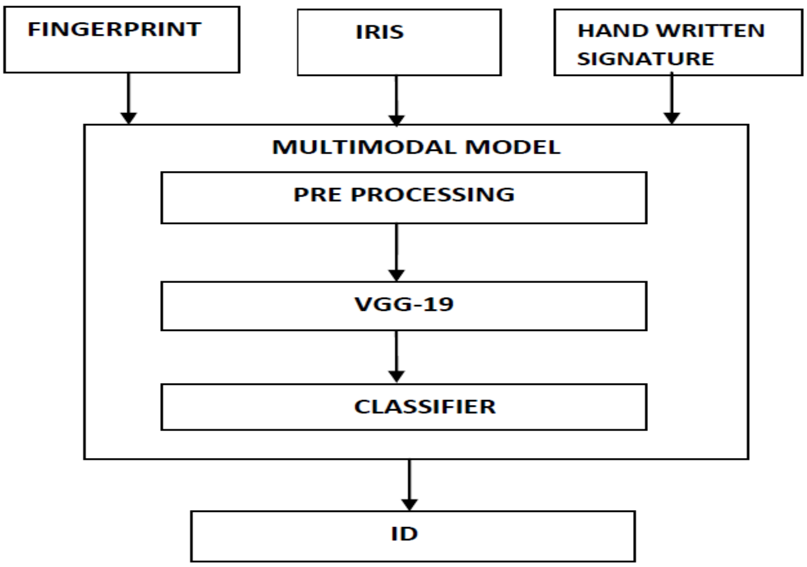

Fig 1. Basic Architecture of Proposed Solutions.

Implementation of the proposed multi modal biometric framework utilizing the three attributes namely iris, finger patterns and signatures, the uni modal iris and finger print recognizable proof solutions that are implicit in past efforts [24] are repeated in current review. In addition, another off line signature single biometrics has been created. At that point forward, the presented multi modal solution is created utilizing the triple single biometrics solutions. After considering the previous work on uni-model solutions, the accuracy of these models are analysed before combining in multi model solution.

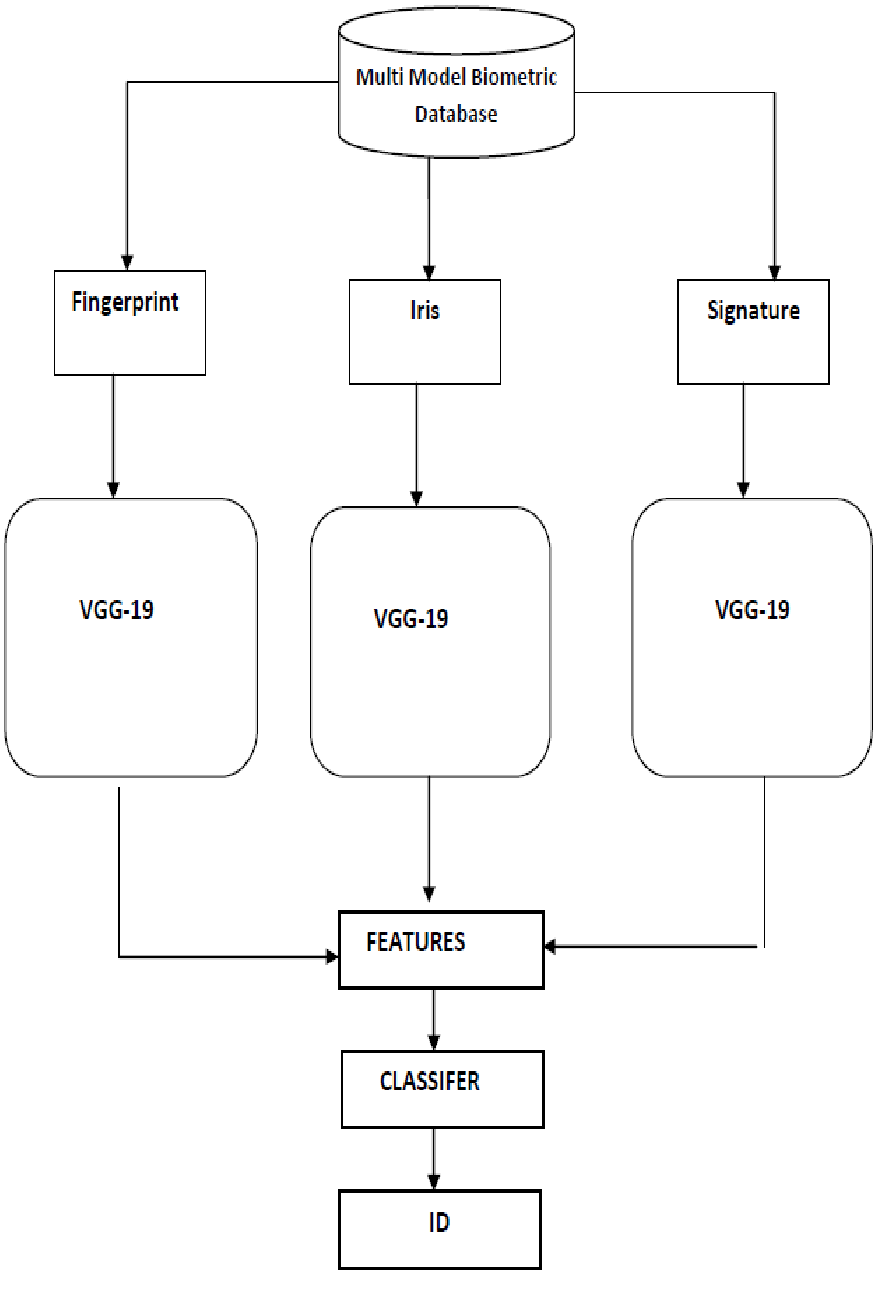

Fig 2. Feature level solution for multi modal approach using VGG-19 net.

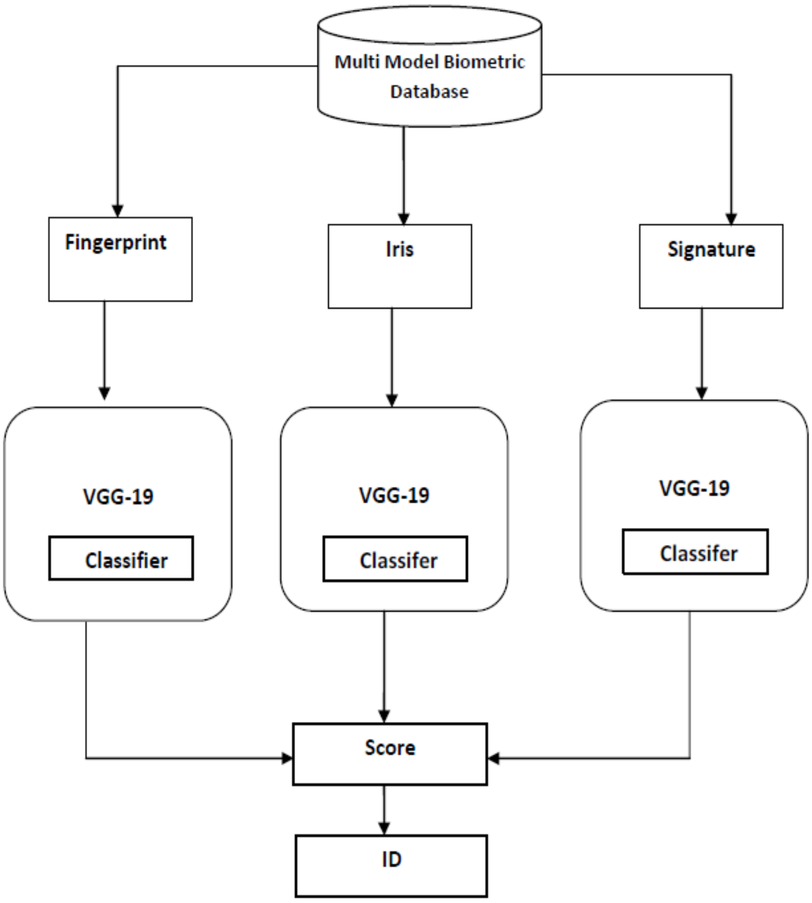

Fig 3 Score- level solution for multimodal Approach using VGG-19 net.

CNN Architecture

In Learning learning, a convolutional neural organization (also called ConvNet) is a class of deep neural nets, most frequently applied to investigate visual images. Presently when we consider a neural nets we give a thought for matrix computation, however that may not be the situation with ConvNet. It utilizes an extraordinary method called Convolution. Presently in math convolution is a numerical calculation on two functions that creates a another function that communicates how the state of one is altered by the other.

Technologically, in a deep learning techniques it is to train and test, each input image passed it through a set of convolution layer for feature extraction using Kernels, Operation of Pooling for reducing size, fully connected layers for vector transformation and apply Softmax classifier for classification of an object. While preparing VGG-19 net , two sorts of spread utilized, known as for ward propagation and back propagation. For ward propagation includes the net taking picture info and set channels and different boundaries parameter on an irregular premise. The info is then spread for ward to the network and uses the irregular boundaries to work out the misfortune esteem. Followed by this, foundation empowers the network to utilize improvement strategy for decrease the result misfortune esteem. In the course of this, back propagation, the misfortune worth of the forward engendering is utilized to empower network loads and boundaries are altered, and misfortune worth to decreased as needs be. This readies the boundaries of the following iteration of forward propagation [22].

The main challenge with the CNN model is tuning the hyperparameters to get the expected output. Tuning of hyper parameters need finding out the optimal value of hyper parameters of the algorithm, since hyper parameters are having total training variables of the framework of the technique or set of training rules. Hyper parameters includes: Learn rate, no of epochs, drop-out value, L1 & L2 regularization , batch equalization and batch length.

The VGG-19 a pre-trained network to recognize human eye iris, finger print and signatures is chosen because it leads a easy network design, and it is highly recommended utilized in deep network approach till present [22], VGG-19 have input size 224x224x3. VGG-19 comprised of 16 convolutional layer, 5 pool layers, followed by 3 completely associated layers, as displayed in fig 4. The initial conv layer utilizes 64 channels of length 3X3, and the size of the came about characteristic map is 224x224x64. VGG-19 uses Rectified Linear Unit. which is classified as a non-linear activation function that pass away the result of the conv layer to a non-linear result. ReLU substitute its negative value with zero , and it is characterized as:

$$F=MAX(0,X) \qquad (1)$$

Where , convolutional layer is the output X.

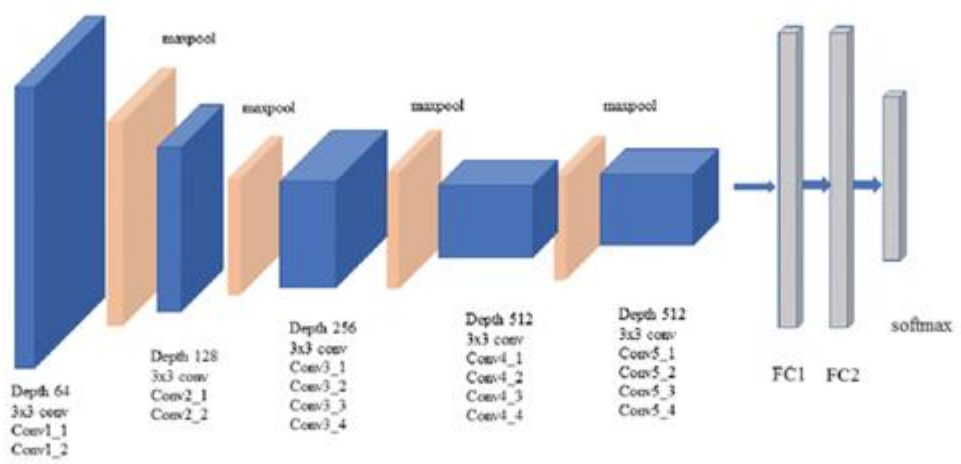

Fig 4. VGG-19 Network Architecture.

The softmax function is sometimes called the soft argmax function, or multiple class classification function. It takes input vector of p real numbers where p is comparable to the no of classes, & afterward to normalise the contribution to matrix vector of values that follows a likelihood conveyance whose absolute summarizes to 1. The result values are somewhere in the range of zero and one, which obliges many classes in the neural organization techniques. Soft max function ascertains the possibilities of one and all class over every conceivable class, and that has the higher likelihood is the objective class. Soft max equation applies the escalation function to every component in the vector form, and afterward standardised these values by division of the summation of all the escalations as the following equation::

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Where zi is parameter in z input vector form and j is j th class.
Output value vector from the soft max function can be represented by following equation

Soft max result = [S1, S2, ………,Sn]

Where, Si is the chance of being part of the data repository to the j class.

To construct our CNNs models utilizing VGG-19, the initial four squares in VGG-19 loads were frozen, as the base layers' channels look for low-level elements, like points and lines, inside the pictures. The highest layers is only trained when there are the filters search for high level feature values.

Fusion Methods

Fusion at Feature stage It involves the fusing of feature be in tune with to multiple traits. The three traits are to extract features and are merged to create fresh features that identify the individuals. In this merging technique, the solution learned the way to recognize the combined characteristics during the training stages. The results of the 2nd fully connected layers of the human eye iris, finger print and signature CNNs network are fused. The characteristics vectors that resulted from the 2nd fully connected layer of the triple CNN frameworks become single vector, which can be described as follows :

$$a= a_r|a_f|a_s$$

Where a_r is the selected characteristics of the human eye iris image, a_f is the derived qualities from the finger print image and as is the qualities derived from off line signature images.

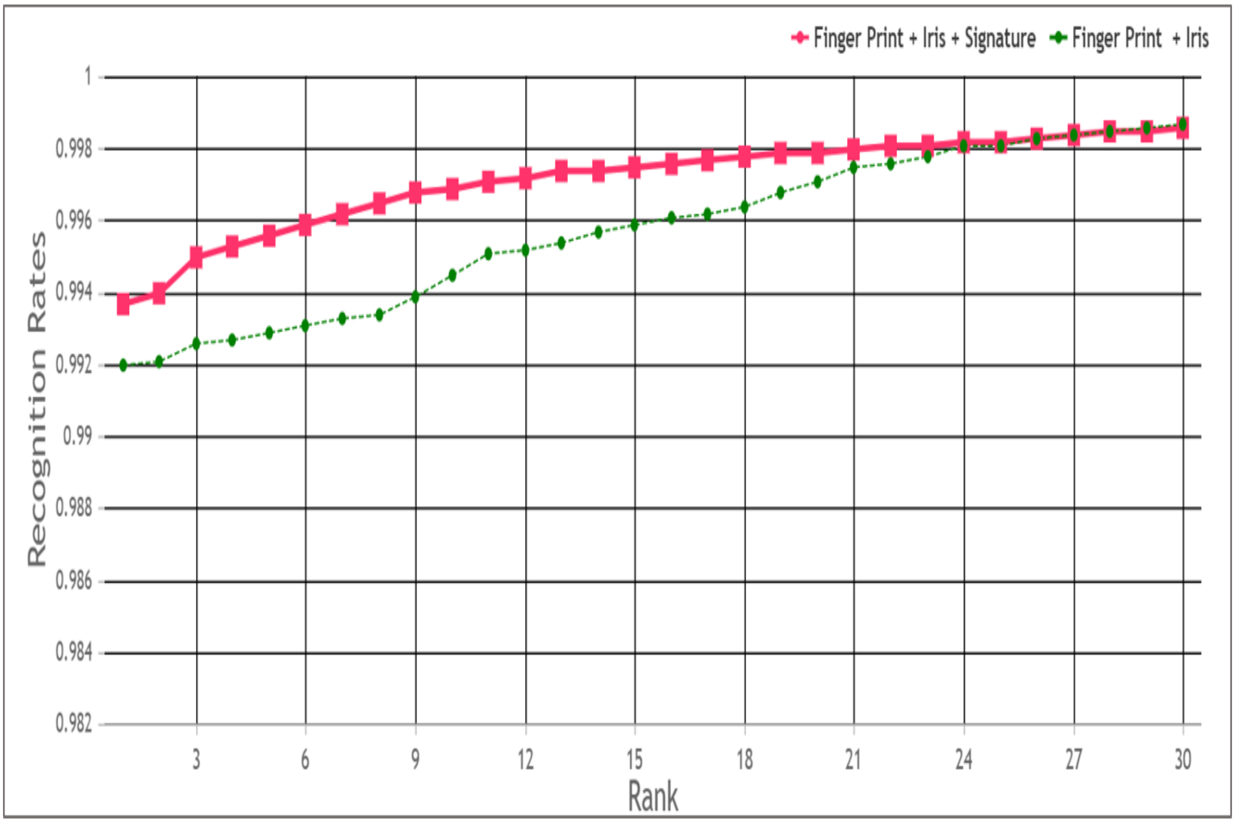

Fig 5 Fusion at Feature Level.

The output vector is passed into the softmax classifier, which classifies the image on the basis of the similarity score and then recognizes the identity of the user.

Fusion at Score Stage- In the score stage merging techniques, the result of the 2nd completely associated layer of every CNN network for human eye iris, finger print and off line signatures are passed in to its soft max function to get the matching values.

Fusion at Score stage procedure has two stages. The initial pace was normalizing the count value came about form of every CNN network, & afterward the matching value of the VGG – 19 networks were melded utilizing a matching value combination technique. At long last, the model results the personality of the individual whose combined score maximum

Two different score fusion techniques, to be specific, the number arithmetical mean rule and product-based rule combination has been utilized. The arithmetical mean rule sums up the matching values of every single characteristic, the product are divided by the quantity of attributes, along these lines giving a final score.

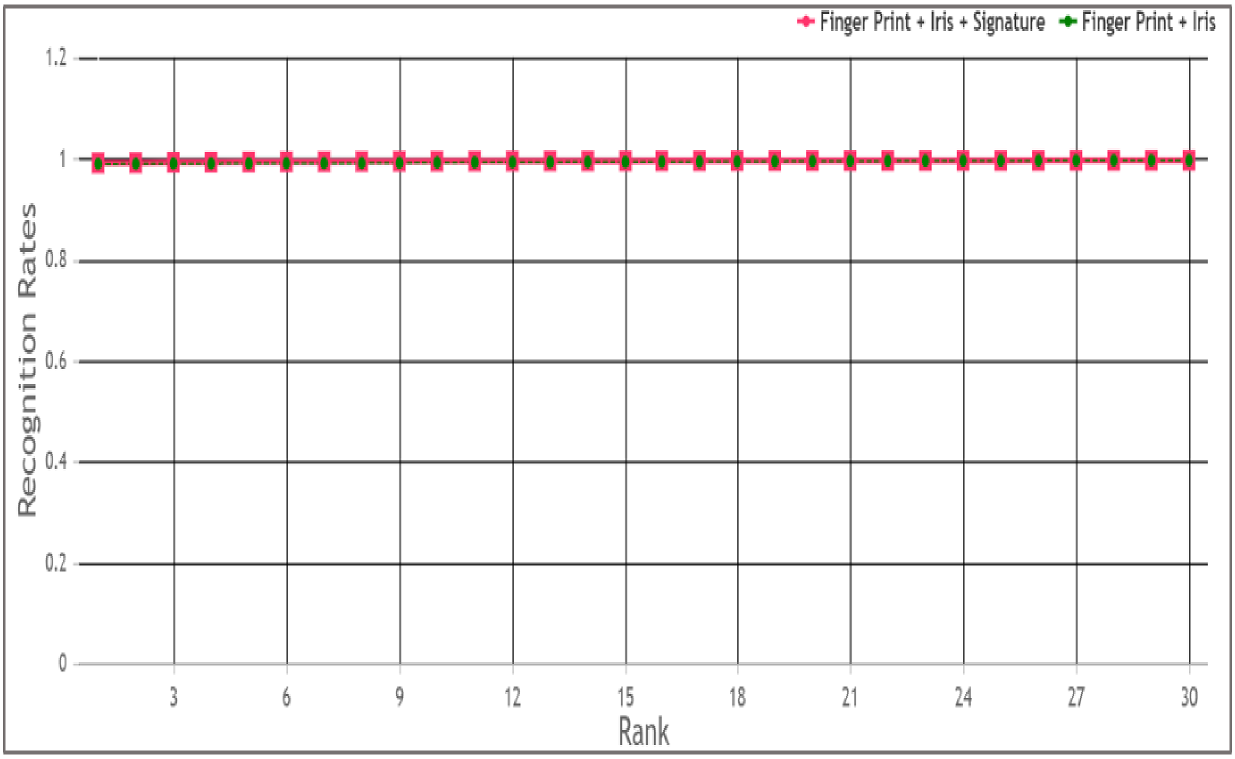

Fig 6 Fusion at Score Level.

The arithmetical mean rule calculations are applied following equation:

$$S = \sum St / j$$

Where St is the score vector of the trait t, and j is the number of traits.
In the product rule, the fused score is calculated by multiplying the score of the three traits. It calculated as:

$$\prod_{t=1}^{j} St$$

Here,

St =the matching value vector of the traits,
J= the number of traits.

IV. RESULTS AND ANAYSIS

The solution is using the google tool, which is a deep neural network approach and allows subjects to execute the source code in a anchored CPU. For development ,Keras Python library of the solution used.

Previous work , image of the every subject in SD UMLAHMT repository were separated haphazardly in to preparing, approval, and test set utilizing various rates (60/20/20), consequently, in this exploration, the information of every subject is isolated into 60/20/20, for preparing 60 percent, for approval 20percentand for testing 20 percent.

The repository pictures were coordinated into triple organizers to preparing, approval, and test and every envelope possesses the examples for every subject. The preparation data was utilized for preparing and to fit the deep learning network for utilizing proceeded ahead and in reverse goes via it, while the approval set was to assess the last model fit utilizing the forward pass as it were.

Framework assessment procedure zeroed in the rightness of client distinguishing proof, that can be estimated through the precision metrics. Exactness to be used in assessing the represented network and investigating the impacts of the distinct hyper parameters. It tends to be determined as the proportion of accurately arranged pictures to complete nos of pictures.

$$\text{accuracy percent} = \frac{\text{Nos of truely grouped pectures}}{\text{Total nos of pictures}} \text{X } 100$$

HAND WRITTEN SIGNATURE METHOD- It is one of the most popular biometrics trait in day today authentications. With the recent development of deep learn network and artificial neural nets, the research on handwritten signature recognition is also becoming advanced. In terms of signature data collection methods, there are mainly two kinds: offline signature image and online signature data. Offline signature image refers to the handwritten signature in this literature, which is then transmitted in the repository through the electronic device to form the signature image, and then verified according to the image features.

The design of the hand written signature image deep model is equivalent to VGG -19 network with adjustment that may be applied to keep away from the over fitting problem. A cluster of standardization layer after every completely associated layer was submitted. L2 regularisation was submitted to the completely associated layers and tune to value of 0.0001. One drop out layer prior the grouping was additionally submitted and pre-defined value of 0.3. The solution was prepared utilizing a group size of 32, with a learn pace of value initialised to 0.0001 and 25 ages.

For objective to approval, right off the bat, the solution was tried utilizing the FV- USM dataset [25], which store just signature pictures data. The solution accomplished a precision pace of 98.78 percent with FV-UVM repository and an exactness of 98.31% on the SDUMLA-HMT dataset is utilized.

RESULTS OF MULTI MODAL MODEL

The multi biometrics model was made of intertwining of the triple unimodal traits: human eye iris, finger print and signature images. The accompanying sub section show the investigations of the applied multiple combination draws near. Feature stage Fusion preparing the multi biometrics solution, multiple variables are thought of, including learn rate, bunch length, and drop out values. It is observed that the best solution has been acquired after the learn rate boundary is adapted to a threshold value of 0.0001, a 64 group size is chosen. Drop - Out layer, with a pre-set value of 0.3, was submitted before the classifier module. The Adam and Cross Entropy strategies are utilized for improvement and misfortune work. The presented multi biometrics solution with attribute stage methodology accomplished a precision pace of 99.39%. Score stage merger arrangement match value of iris, figer print, and off line signature solution were joined utilizing two different matching value combination techniques: Math mean rule and product match stage rule. The precision worth of the framework when above techniques were utilized achieved 99.67 percent.

The ID precision consequences of the directed trials are summed up in table 1 for the unimodal and multimodal models, individually. The outcomes show that higher precision rates were acquired by the multimodal biometric model in contrast with those of unimodal models. This shows that, as initially proposed, multimodal biometrics gives a profoundly successful method for further developing the exactness paces of a biometric framework. For example, the created finger vein unimodal model got a distinguishing proof precision of 98.38%, which was not exactly the exactness of the proposed multimodal model (99.39%).

Table No 1 Performance of multimodal fusion

Model	Fusion	Accuracy
fingerprint & iris	Feature stage fusion Score stage fusion (AM & PR)	99.22% 99.88%
Iris, fingerprint and signature	Feature stage fusion Score stage fusion (AM & PR)	99.49% 99.57%& 99.78%

A differentiation among the accomplished consequences of the presented multi biometrics with the after effects of past task [24] is made in view of the sort of combination algorithms utilized, as displayed at Table No .1. For the element combination algorithm, it is actually quite important that the multi modal biometrics solution utilizing the triple biometry characteristics matching value of 99.49%) outflanked the multi modal solution of the twin attributes (matching of 99.32%). For the most part, a higher verification precision was gotten by combining three qualities contrasted with the presentation dependent just upon a couple of attributes in the dynamic interaction. For the matching value combination approach, the proposed model and our past model in [24] acquired a similar outcome (match value of 99.57 percent). It very well may be seen that the average rule and the number arithmetical mean strategies accomplished similar outcomes. It can be clarified by the way that the two techniques are procedure-based match value combination strategies, and that implies that they are fixed and not prepared guidelines.

An exhibition correlation was done among the presented solution and our past task in [24] in view of the attribute combination technique, as displayed in Cumulate Match Curve (C.M.C) graph in fig 5. As should be visible from the graph, the presented strategy has accomplished preferred outcomes over our past model in [24]. Rank-1 distinguishing proof exactness more prominent than close to 99.22 percent has been accomplished of 99.11 percent has been accomplished by our past model [24], while the presented solution accomplished a rank one ID precision of 99.49 percent

To the extent of my knowledge there, no one in past investigations that have implemented multi modal biometric solutions for distinguishing an individual utilizing three characteristics, as one of trait is handwritten signature. Also, there is no work in the writing that utilized the SDUMLA-HMT dataset for assessing a deep learning network in recognizing an individual situated in a similar triple biometric characteristics are utilized in current review. Accordingly, the presented multi modal biometric solution was contrasted and the past review [14] that utilized the SDUMLA-HMT dataset in fostering a solution for distinguishing individual in view of right iris, left iris, and finger print attributes. Additionally, the presented multi biometrics solution is contrasted and the another two past examinations in the work [15], the pre-owned triple distinct characteristics of various biometry framework utilizing various datasets. Table No. 2 indicates the correlation results among the presented solution and various past solutions.

Even if the multi modal biometric framework described in work [14] had the option to get 99.11 percent recognizable proof value, it is because of the way that for applying numerous pre - handling procedures on image pattern to distinguish explicit regions prior to embedding the picture into the deep learn technique. It is a tedious cycle, that builds the solution processing time. Furthermore, the precision value recognizable proof network, that depends to the Deep Learn Network technique [14] was 85.34 percent. Be that as it may, the multi modal framework [14] depended to a greater degree toward the brilliant design of right iris and left iris VGG-19 calculations to the combination interaction to accomplish high acknowledgment precision. Besides, our face recognizable proof model precision outperformed the exactness of the facial ID solution of [14], i.e. VGG-19 calculation shows better results compared to the Deep Learn Net method.

V. CONCLUSIONS

In present research a multi biometrics traits-based solution was implemented for authentication of every individuals. The proposed solution utilized the convolutional Neural Network type of deep learning models. From the three biometric fingerprints, human eye iris and off line signature characteristics of a person used in feature stage and score stage merging for user identification. To the best of my knowledge, this combination of three biogenic traits using deep learning techniques is first. The model was tested using the SDUMLA HMT repository. In score stage merging we achieved 99.1 percent accuracy and in feature level fusion 98.4 percent accuracy.

The results are showing performance improvement of the VGG-19 net. In terms of future research, it is better is we build CNN model basic primary of the deep networks that are more efficient for each biometric instead of utilising a pre trained solutions. Offline signature can be pre-processed for reducing the load on model.

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