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Unimodal biometric identification system on Resnet-50 residual block in deep learning environment fused with serial fusion

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ABSTRACT

Purpose: Multifactor authentication biometric identification systems are tending on high, advance across the globe, and are significant in every sphere of life, financial business transactions, access control systems, cross-country border gateways, etc as security measures can not be ignored. So, robust multimodal identification systems are globally accepted and continuously upgraded with technical innovations by researchers, and technologists to protect from spoof cyber-attack and security breaches. Multimodal systems are difficult to manipulate, and breach the security layer due to tightly coupled verification feature passcode used due to concatenation on fused feature vector build-up by extracting important features of multiple traits that's the basic robustness of the system. In this proposed model we have experimented with fusing four biometric traits i.e. facial, fingerprint, and hand-written signature together to make robust system.

Design/Methodology/Approach: The proposed model developed on Resnet-50 residual block base architecture was developed, executing the serial fusion algorithm for concatenation of important features forming fused feature vector (Fm) and experimented with two hundred fifty samples of each subject in deep learning environment.

Finding: The finding of our research experiments is that handwritten signatures have the highest technical feasibility for the concatenation of biometric feature with facial, fingerprint & Iris traits.

Originality /Value: Multimodal identification system has great impact & value, in terms of social security at individuals as well as social, economic & multi fold angel. In this research paper, original scenario of real life have been incorporated like hand written signature concatenating with facial, fingerprint & Iris traits for verification of identification in off-line mode and country cross boarder gateways & others.

Paper Type: Empirical Research Paper.

KEYWORDS: SerialFusion | Fused Feature Vector | Resnet- Residual block Network | Skip Connections | Hyperparameters | Outlier-IRT

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Introduction

Unimodal systems are prone to breach security levels in comparison with the multimodal system due to the lack of a combined verification key with each trait that's called multifactor authentication. It is obvious to explore a highly secure, robust multimodal identification system and develop an optimized algorithm on the proposed feature fusion system.

In this research work experiments have been proposed to find out the highest probability & scope of feature fusion towards biometric traits like a facial, fingerprint, Iris with handwritten signature & voice, etc based upon physiological or behavioural characteristics.

The major limitation of machine learning techniques is related sensitiveness of training data and parameters as changes in training data can lead to producing different results.

In the machine learning technique, important features are extracted manually and experimented on training model separately which involves cumbersome efforts & time consumption, first train's system is with known labelled data (where input–output mappings are given), then the system is used to perform the required operations on unlabelled data based on its experience.

Even in today's scenario, the banking sector is prevailing a common practice of matching customer face with their hand-written signatures manually for matching of the handwritten signature by comparing with the already stored customer's signature & photo in the bank's database repository by the desk officer at the counter. In rural areas, the Indian population is not much familiar with digital technology like digital or e-sign access. The process of feature passcode matching is called double key authentication factor and our research objective is to automate the manual process by concatenating feature vectors corresponding to face, fingerprint, iris & handwritten signature by developing algorithm & process optimization.

In deep learning, feature extraction, concatenation, summation, and training model are concurrently executed dynamically producing results with less error of margin, and such technique has emerged as highly lucrative, positive result orientated which encouraged the author to explore, and experiment with the research work in deep learning environment feature fusion techniques on multiple traits like face, fingerprint, Iris, and handwritten signature on Resnet-50 architecture which is superior to earlier research work implemented on VGG-16, VGG-19, CNN classifiers base architecture.

Literature survey

A survey study was conducted on recent research papers published related to face, fingerprint, Iris, and hand-written signatures based on machine learning techniques and CNN deep learning classifier base models. A comparative chart of accuracy performance vide Table-1 has been depicted related to machine learning, deep learning fusion with handwritten signature with research analysis trends evaluated based on datastatistics.

Figure-1: Comparative Accuracy Summary

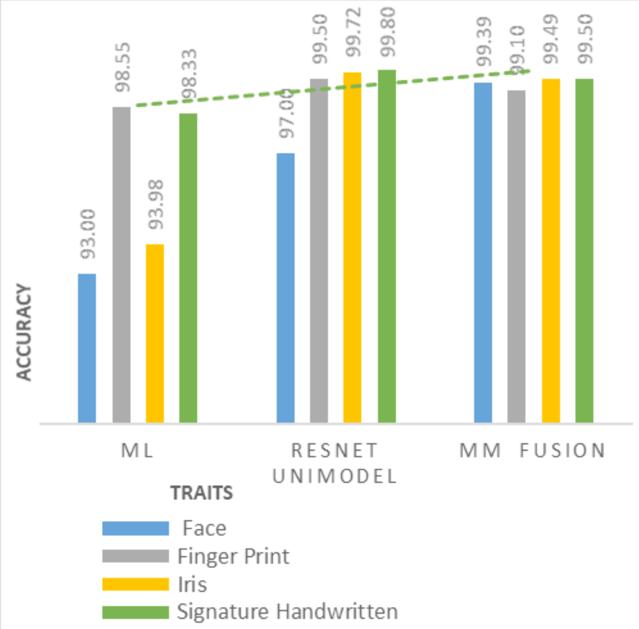

FIGURE-1 : (COMPARATIVE ACCURACY SUMMARY)

The trending line of figure-1 shows that under unimodal, accuracy performance parameter of handwritten signature consists of high technical feasibility in support for fusing feature vectors with other traits like face, and fingerprint. & Iris.

(Mustamin Anggo[1] and La Arapu[1],2018) implemented face recognition work using the fisher face algorithm, and machine learning techniques PCA on the Papuan image database and achieved an accuracy rate of 93.00(%) percent on testing, training model accuracy performance was 100 percent in the Matlab environment.

(Arshi Husain[1] and Virendra P. Vishvakarma[2], 2022) experimented the research work related to facial recognition on Resnet-152 V2 architecture that's capable to deal with non-linearity for identity mapping and used AT&T facial database, executing Adam optimizer & SoftMax activation function, observed the validation performance accuracy @97.00(%).

(Justice Kwame Appati[1], Prince Kofi Nartey[2], Ebenezer Owusu[3], and Ismail Wafaa Denwar[4], 2021) implemented the wave atom transform technique for Smoothing framework on minutiae features framework works for fingerprint identification and analysed the performance accuracy level 98.55(%).

(Mamadou Diarra[1], Ayikpa Kacoutchy Jean[2], Ballo Abou Bakary[3], Kouassi Brou Médard[4], 2021) experimented with his research work related to fingerprint recognition on Resnet-50 algorithm base architecture in the deep learning environment with SOCOFing database and observed accuracy level 99.50(%). The Stochastic Gradient Descent (SGD) optimizer was used to maximize the weights & biases using feed forward and backward propagation.

(Yasir A. Jasim[1], Ayad A.Al-Ani[2].Laith[2]A.Al-Ani[3], 2018) research work was related to Iris Recognition using Principal Component Analysis (PCA), CASIA V3i database, and euclidean distance for classification purposes. The results were normalized by the dogman rubber sheet method, accuracy was recorded at 93.98%.

(Smita Khade[1], Shilpa Gite[2], Biswajit Pradhan[3], 2022) research work was designed on ResNet-50 architecture, for Iris liveness detection using multiple deep convolution networks and Clarkson, 2015 database, 80:20 for training, validation purpose, during training data augmentation (DA) such as flopping & rotation technique was used to reduce the risk of overfitting. The accuracy was observed at 99.50(%) on Resnet-50 architecture base mode.

(Mariusz Kurowski[1], Sroczynski[2], Georgis Bogdanis[2], Andrzej Czyzewski[2] 2021) table-3, experimented with an off-line signature identification technique using a histogram of oriented gradients (HOG) features on generalized regression neural networks (GRNN). PCA signature dataset, and observed the accuracy at 98.33(%).

(Ahmad T. Al-Taani[1] and Sadeem.T. Ahmad[2], 2022) executed the experiments related to research work on the recognition of Arabic Handwritten Characters using Residual Neural Networks and MADBase and observed the accuracy performance at 99.80(%). The enhanced performance was observed due to the implementation of Skin Connection Architecture inherently built with Resnet-50.

Fingerprint (Kwame Appati[1], Prince Kofi Nartey[1], Ebenezer Owusu[1], and Ismail Wafaa Denwa[1], 2021), Iris (Yasir A. Jasim[1], Ayad A. Al-Ani[2].Laith[2] ,A. Al-Ani[3], 2018), Handwritten Signature (Zainab Hashim[1], Hanaa M. Ahmed[2], Ahmed Hussein Alkhayyat[3], 2022) and CNN classifier over deep learning (DL) group is reflected face (Arshi Husain[1] and Virendra P. Vishvakarma[2], 2022), Fingerprint (Mamadou Diarra[1], Ayikpa Kacoutchy Jean[2], Ballo Abou Bakary[3], Kouassi Brou Médard[4], 2021), (Iris Smita Khade[1], Shilpa Gite[2], Biswajeet Pradhan[3], 2022), Handwritten Signature (Zainab Hashim[1], Hanaa M. Ahmed[2], Ahmed Hussein Alkhayyat[3], 2022). Feature Fusion of handwritten signature has been mentioned, fingerprint with online signature (Mehwish Leghari[1], 2021), Fingerprint with Iris and handwritten signature (Ashok Kumar Yadav[1], Prof. T. Srinnivasulu[2], 2021), handwritten signature with CNN hybrid architecture (Poornima Byahatti[1], Sanjeev Kumar M. Hatture[2], 2017), and automated method of the handwritten signature over the neural network employing feature fusion.Technique (Mariusz Kurowski[1], Sroczynski[2], Georgis Bogdanis[2], Andrzej Czyzewski[2] 2021).

(Nada Alay[1] and Heyam H. Al-Baity[2], 2020) experimented & explained that observed the accuracy performance on an increased scale above 99.39% deploying feature fusion level techniques by concatenating the facial, Iris, and finger vein on VGG-19 architecture in a deep learning environment.

(Mehwish Leghari[1], Shahzad Memon[1,2], Lachman Das Dhomeja[1] and Akhtar Hussain Jalbani[1,2] and Asghar Ali Chandio[2], 2021) experimented with deep feature fusion of fingerprint & Handwritten Signature for Multimodal Biometrics. The accuracy performance was observed @99.10%, validation accuracy_97.00%, with fivefold cross-validation, 96.00% with ten-fold cross-validation techniques with an early-stage feature fusion scheme. Whereas, performance was 95.00% with a late fusion scheme and cross-validation with five and ten-fold together.

(Ashok Kumar Yadav[1], and Prof. T. Srinnivasulu[2], 2021) related with fusion of multimodal biometric of fingerprint, Iris, and handwritten signature traits using deep learning technique on the VGG network. The SoftMax function used for the multi-class classification function, accuracy performance was observed at 99.21% on future fusion feature vector. Cross-validation technique used based on ratio 60: Training,20: Testing,20: Validation.

(Tiffanie Edwards, 2021) claimed that combining the deep learning technique with the serial fusion method improves the accuracy of verification systems, significance convenience to genuine users and achieved AUC_0.9996 with proximity to the ideal value one (1).

(Poornima Byahatti, 2017) stated that the trend towards combining multimodal data in real-life biometric authentication applications is more secure than the unimodal authentication systems. Feature fusion of various biometric data is the key to multimodal biometrics and fusion can occur at various fusion levels, feature level, score level as well pre or post-sensor level fusion.

A review of the literature indicates the accuracy performance on feature fusion of handwritten signature and other features like fingerprint, Iris trending upward consistently more than 99%. supporting the technically feasible ground for the scope of feature fusion exploring viability with multiple traits like a handwritten signature, voice embedding, etc on proposed research work.

Multimodal biometric systems are capable to defeat various limitations of unimodal biometric systems because sources of different biometrics typically compensate for inherent limitations to one another. On literature survey records fusion of multimodalities in the deep learning environment is encouraging, consisting of the scope for experimenting with frameworks, developing algorithms on research objectives concatenating facial fingerprint, Iris, Handwritten signature, and embedding voice together to develop a more robust, secure system

Table-2: Performance parameter of Handwritten Signature

ACC	Classifier	Data Set	Reference	
92.30	VGG-16	GDPS	Table-3, Bonde et.al,	
87.00	Neural Network	GDPS	Table-1, Binary Feature-14 by Larkin	
78. 00	Neural Network	GDPS	Table -1, Grid Feature-11, by M Taylan	
82.66	Neural Network	GDPS	Table-1, Global Feature, -MaxHistogram, Normalization Area of Signature	
EER- Equal Error Rate				
6.81	Resnet	GDPS	Table -3, Mesra et.al,	
5.67	KNN	GDPS	Table-3, Forozandeh, et, al,	
FAR/FRR –False Acceptance Rate / False Rejection Rate				
FAR	FRR	Classifier	Data Set	Reference
4.16	7.51	Neural Network	GDPS	Table-1, Shashi K.D,
14.70	20.00	Neural Network	GDPS	Table-1, Global Feature, Max Histogram, normalisation Area of Signature Zuraidasahana et.al
6.80	14.00	KNN	GDPS	Table-1,Geometric feature, Zuraidasahana et.al
12.00	16.10	Neural Network	GDPS	Table-1, Geometric feature, Zuraidasahana et.al

The performance of the proposed unimodal, each trait will be evaluated before fusion by concatenation or summation method for four traits i.e. face, fingerprint, Iris & handwritten signature in offline mode using CNN classifier, reduces architecture complexity, overfitting mitigation and ease of data augmentation to learn automatically, adaptively spatial hierarchies of features through feedforward, backpropagation using multiple building blocks, such as convolution layers pooling layers, and fully connected layers in the reviewed paper by (Rikiya, 2022).

To the best of the author's knowledge research work on concatenation among four different traits together like face, fingerprint, Iris, and handwritten signature in a deep learning environment is yet to be explored.

Methodology &Proposed Model

- **Feature level fusion**

The experiment on feature fusion shall be implemented for extracting important features applying dimension reduction technique on each trait separately like face, fingerprint, Iris, and handwritten signature in CNN deep learning environment and performance of accuracy & other hyperparameters used prior concatenating multiple features i.e. face, fingerprint, Iris & handwritten signature together forming singular fused vector through serial fusion method. Serial fusion can be applied pre or post-sensor level fusion and geniality of legitimate identification shall be accessed based on falls acceptance ratio (FAR) & false rejection ratio (FRR) based on thresholding parameters. Performance parameters of a fused vector are evaluated on training, testing & validation exercising over the entire dataset on the proposed model.

- **SerialFusion Technique**

The serial features fusion technique is used toform a fused feature vector in a singular matrix and weighted serial feature combined with corresponding feature vectors i.e. face, finger vein, iris & hand-written signature using a weighted serial feature fusion algorithm. After normalization, a fused feature vector ($F_m F_m$) is formed by optimization over the filters of each neural network layer using concatenating each trait serially and calculating mathematical value in binary form of zero(o) or one (1) correspondingly declare as imposter orgenuine.

Normalized fused feature vector ($F_m F_m$) is formed by optimization over CNN filters by neural network layer using concatenation technique.

(i.) $F_m \leftarrow [F_a \cup F_b \cup F_c \cup F_d] \cdot W^T + b$
$F_m \leftarrow [F_a \cup F_b \cup F_c \cup F_d] \cdot W^T + b$, where(u) refers the union of feature vector,

(i i .) $F_m \leftarrow \left[\frac{F_a, F_b, F_c, F_d}{4}\right] \cdot W^T + b$
$F_m \leftarrow \left[\frac{F_a, F_b, F_c, F_d}{4}\right] \cdot W^T + b$, where $[\frac{F_a, F_b, F_c, F_d}{4}\frac{F_a, F_b, F_c, F_d}{4}$] refer to the average feature $F_m F_m$; and F_a, F_b, F_c F_a, F_b, F_c, and $F_d F_d$ represents corresponding fused

feature vector of face, finger vein, iris & handwritten signature of human traits abstracted through sensor and W^T tends to weight transpose, b represents bias
W^T tends to weight transpose, b represents bias.

(iii.) The feature fusion can be expressed using the operation $\oplus$, i.e., $F_m = [\![(F]\!]_a \oplus F_b \oplus F_c \oplus F_d)$ $F_m = [\![(F]\!]_a \oplus F_b \oplus F_c \oplus F_d)$. Finally, a classifier C is applied that maps $C = F_m \rightarrow Y'C = F_m \rightarrow Y'$, where $Y'Y'$ is the predicted class label of the training sample.

(iv.) Discriminative features extracted from images from sensors expressed mathematically,

F_i = f(X_i) = f_m; w_m (⋯ (f_2; w_2 (f_1; w_1 (X_i)))
F_i = f(X_i) = f_m; w_m (⋯ (f_2; w_2 (f_1; w_1 (X_i)))

Data acquisition & pre-processing algorithm, before classification, development of multimodal feature vector stepsfor data pre-processing is shown below -

- Decode the JPEG content to RGB grids of pixels with channels.
- Convert these pixels into floating-point tensors for input to the neural network.
- Rescale pixel values (between 0 and 255) to [0, 1] interval for the training of neural networks within therange to learn efficiently.

The relationship between pixels is preserved by using a convolution filter at the kernel level, a kind of small grid that stores pixel values and perform different operation such as sharpening, edge detection, blur, etc. on small squares of input data.

CNN performs dimensionality reductionby processing feature mapsextracting importantfeatures on the most significant pixel value at each filter patch of the feature map at the input pooling layer executing the activation function (figure-1), thereafter extracted features are mapped through fully connected layer into the final output on binary decision i.e.0 or 1.

In our proposed model, Resnet-50 architecture has beenimplementedto tackle the vanishing gradient problem during backpropagation, as the value of the gradient decreases significantly which leads to restricting any visible, significant changes to weights.This issue is resolved by introducing the Resnet structure that uses "skip of connection" a direct connection that skips over some layers of the model.Resnet activation function, F() output is represented, F(w*x + b) (=F(X)), Equation .... (1) Resnet trains the output F(X)=0, where Y=X.

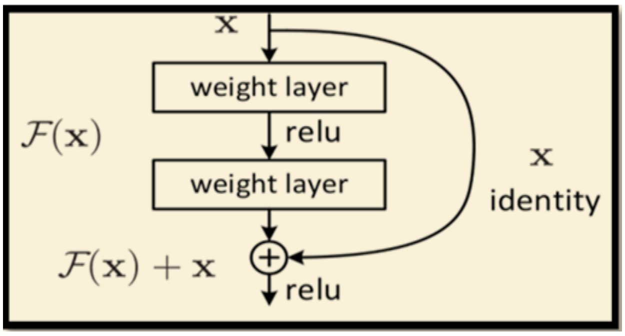

Figure-2: Single Residual Block with Skip Connection

Non-existence of skip connection structure, input 'X (ResNet-Skip connection framework), gets multiplied by the weights of layer followed by adding a bias term. Relu activation function works Ranging from [0 to infinity].

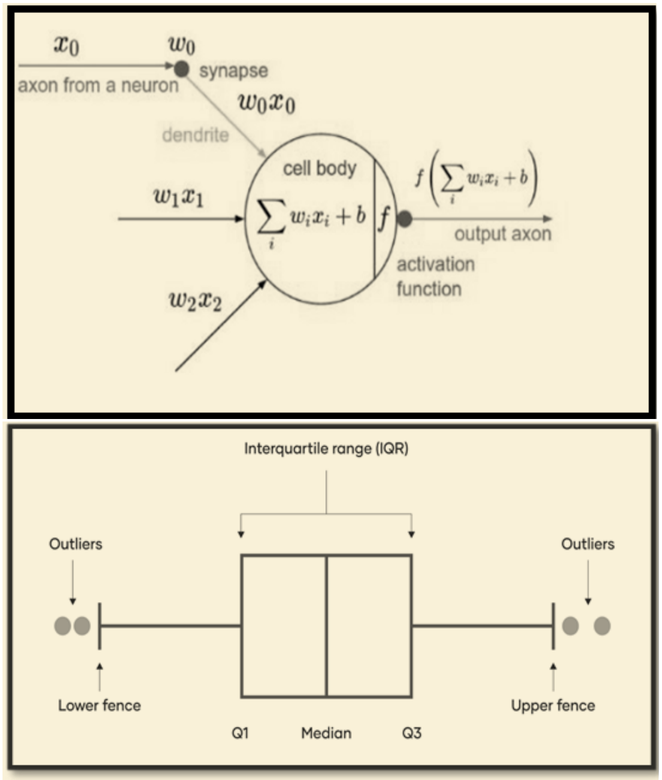

Figure -3: Activation function of CNN framework

At the input layer, separate filters are applied and feed-forward propagation & backward propagation algorithmsare triggered at the hidden layer to achieve desired accuracy performance. Finally, classification of the fused feature vector as an output delivered based on categorical entropy for binary decision i.e. either 0 or 1 level for identification label.

where, w=>weight, b=>bias, x=>feature, f=>activation function

In our experimental model, KNNensemble classifier parametric algorithm is used which calculates the similarity between all data points and projected new data points based on Euclidean distance (Ed).

$$d(\mathbf{p},\mathbf{q}) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \text{ Equation……… (2)}$$

Here, K refers the parameter to nearest neighbors to be included in the majority of voting, (p, q) implies two points of Euclidean n-space, and (q_i& p_i) are Euclidean vectors, starting from the origin of space (initial point) n=n-space, d=distance between two data point q and p of the dataset, square root used to minimize the error, also called residual error. Cross-validation technique used to estimate the expected level of best fit-in approach over entire data sets used for training of model and data is model-independent.

In our experimenting model, the k-fold dataset validation method has been applied for calculating the mean average for the accuracy value of data sets for evaluation of modal performance on training, testing, and data validation purpose, preferred acceptable value of "K" is kept as 5 that's not low or high even data point to outlier boundary or too specific data point of the general model.

- **Handling Outlier Overfitting**

True outliers are present in variables with skewed distributions where many data points are spread far from the mean in one direction

True outliers present in variables with skewed distributions where many data points are spread far from the mean in one

- **Figure -4: Outlier Handling**

direction, required appropriate statistical tests or measures for skewed distribution or many outliers. Although, other outliers that don't represent true values also come from many possible sources like measurement errors, data entry or processing errors, or unrepresentative sampling. The outlier's problem was resolved by applying the interquartile range technique (IRT) fordetecting & handling outliers to avoid the bad prediction of accuracy parameters. The outlier's problem was resolved by applying the interquartile range technique (IRT) for detecting & handling outliers to avoid the bad prediction of accuracy parameters. IRT Algorith mappended below-

(i.) Sort the data from low to high

(ii.) Identify the first quartile (Q1), median, and then third quartile (Q3)

(iii.) Calculate IQR = Q3 – Q1

(iv.) Calculate upper fence = Q3 + (1.5 * IQR)

(v.) Calculate lower fence = Q1 – (1.5 * IQR)

(vi.) Use your fences to highlight any outliers and all values that fall outside the fences.

Experiments & dataset

In our proposed model experiments were executed on Resnet architecture for approximately 12000 data samples from the open source repository CIFAR-10 for facial, and finger. Iris & GDPS for signature samples. The subject data set for the test was done on 250individual traits collected from different sensors. Training, testing, and validation datasets for each trait is divided into a 60:20:20 ratio i.e. 60% for training, 20% for validation, and 20% for testing purpose.

The proposed model has been experimented with using forward & backward passes over CNN layers for learning & dropouts to arrive at desired performance for evaluation of the proposed model, exploring effects of different hyperparameters on ResNet-50 residual block-based architecture based performing consistent & data independent Best Fitmodel.

Evaluation of Hyperparameters on Proposed Model Resnet -50 Architecture

The experiment result of the proposed CNN unimodal feature vector w.r.t face, fingerprint, Iris, and handwritten signature traits in the deeplearning environment by tuning hyperparameters are analysed on various matrices as depicted below in Table-3.

Table-3: Hyperparameter

(Feed Forward Network Architecture)		
Layer (type)	Shape	Param
Dense layer		
Total Trainable Params	None, 512, 512, 10	837148
CNN Architecture		
Convolution two delta input layer	None, (26-11-3, 26-11-3, 26, 32-64-128)	400-22195-88627
Batch normalization	None, (13-5-1, 13-5-1, 32-64-128)	128-256-512
Max Pooling layer	None, (13-5-1,13-5-1, 32-64-128)	0
Dense layer	None, (256-10)	40620-3161
Number of epochs	None, (256-10)	25
Batch size	None, (256-10)	32
Total params	None, (256-10)	156310
Trainable params	None, (256-10)	155970
Non-trainable params	None, (256-10)	341
Dropout rate	None, (256-10)	0.04
Training, Testing & Validation		
Training samples	60%	7200
Testing	20%	3600
Validation samples	20%	2400
Total subject 250*12 each trait	-	250

Dropouts layer tuned to reduce overfitting for combination with max- normalization that enhances significantly boosting using dropout method. Implementation of feed-forward propagation (training model) dropout probability i.e. 1-drop probability should be closer to 1, dropout rate @0.8 is treated best-preferred value closer to 1 at input layer. At the hidden layer, the greater the drop probability sparser the model, where 0.5 is considered the most optimized keep probability which states that dropping of 50% nodes. Our experimenting proposed model dropout rate was observed at @0.04 that's a considerably better performance.

A comparative ROC plot corresponding to each trait i.e. face fingerprint, Iris, and handwritten signature is depicted in figure-5, the value of AUC_(0.9) indicates that the proposed model approached towards ideal value One_(1), we can claim that proposed ResNet-50 base architecture perfectly qualify for declaring of "Best-Fit" model irrespective, independent of data.

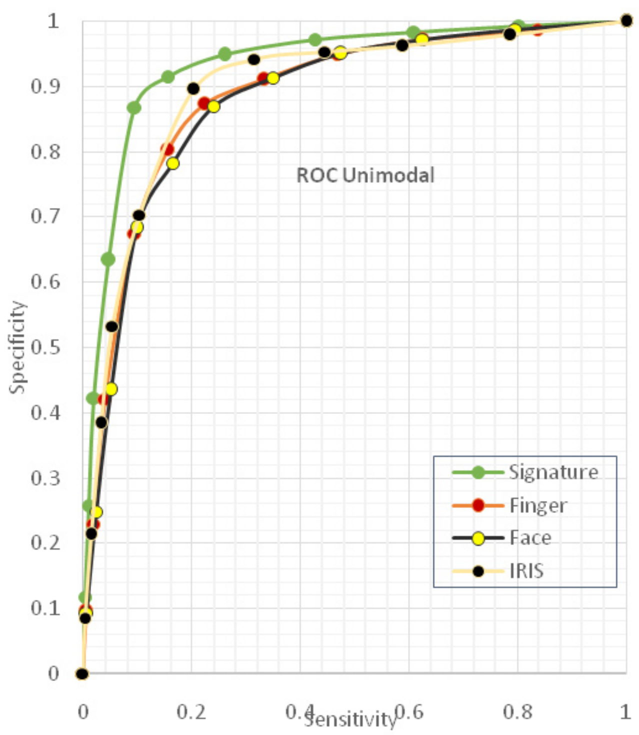

Figure-5: ROC Curve for Unimodal Feature Vector

Results & Discussion

The performance of experimenting results achieved on unimodal *on Resnet-50 base architecture model* evaluated on different parameters on standard formula(s) is indicated in the table-4. It is observed that results related to accuracy performance, AER, EER & FAR, and FRR are fairlybetterin comparison with resultssummarised in the table-2, figure-1 duringthe literature survey for face, fingerprint, Iris & hand-written signature on VGG-16, VGG-19 & another experimenting environment.

Our proposed model on Resnet-50 CNN classifier base architecture has out performed and achieved experimenting results on different performance parameters at the level of accuracy, EER, FAR, FRR, and AUC are tabulated comparatively in Table-5.

Accuracy performanceis relatively on higher scale comparatively comparison withfacial_(99.65>97.00), fingerprint_(99.77>99.50), Iris_(99.81>99.72), and handwritten signature_(99.93>99.80) deployed on residual block network.

In our proposed Resnet-50 architecture base model, accuracy performance w.r.t handwritten signature was observed on higherside ResNet-50, ACC_ (99.93>99.80_ Experimented by (Ahmad T. Al-Taani* and Sadeem T. Ahmad, 2021).

Other performance parameters w.r.t handwritten signature implemented on GDPS dataset are observed with enhanced performance scale, (EER_1.87<05.67),(FAR_01.81<06.81, (FRR_02.66<7.57) and AUC @9.00 approaching towards ideal value One(1) that is considered the BEST FIT Model.

All the experimenting results are relativity on the higher side in comparisonwith previous works implemented by other authors.

The error rate on Resnet-50 algorithm performanceon our proposed model, EER_1.87<1.96 at Serial fusion, (Tiffanie, 2021) <6.81, Table-3, (Mehwish Leghari[1] et.al, 2021) implemented on GDPS synthetic data over the residual network, is quite fair and promising for the fusion of hand-written signature feature with other traits.

Table 5: ResNet CNN Classifier

References	Modalities	Performance	
Recent works on Resnet			
Arshi Husain et. al.	Face	97.00	Accuracy
Mamadou Diarra et. al.	Fingerprint	99.50	Accuracy
Smita Khade et. al.	Iris	99.72	Accuracy
Ahmad Altaani et. al.	Handwritten Signature	99.80	Accuracy
Table-3, Forozandeh et. al.	#	05.67	EER
Table-1, Geometric feature, et. al.	#	06.80	FAR
Table-1,11,Shashi K.D, et. al.	#	7.57	FRR
Our proposed Resnet-50 Architecture Unimodal System	*Face*	*99.65*	Accuracy
	Fingerprint	99.77	Accuracy
	Iris	98.81	Accuracy
	Handwritten Signature	99.92	Accuracy
	#	01.87	EER
	#	01.81	FAR
	#	02.66	FRR

Conclusion

In this paper deep learning Resnet-50 architecture model has been proposedas capable to handle feature reusability, faster convergence, rescaling & skip connections to resolve the vanishing gradient problemand 23 million trainable parameters.Performance accuracy increased by 21% approximately of the proposed model compared withVGG-16&VGG-19 network architecture.

The experimenting result shown vide table no.5 related to the feature of a handwritten signature has outperformed @99.83% among other traits i.e. face, fingerprint & Iris.

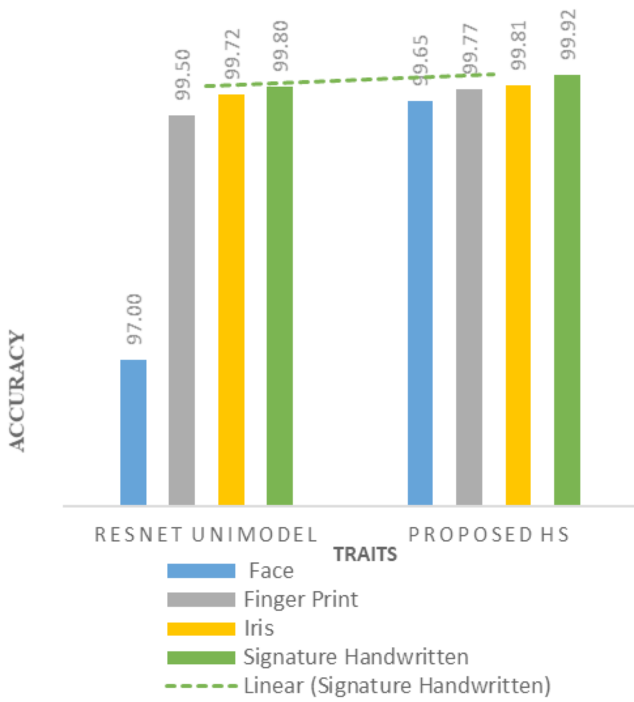

FIGURE-6 :

(PERFOMANCE OF RESIDUAL BLOCK NETWORK)

Given the above, feature fusion of handwritten signature contains the highest technical feasibility for concatenation, and summation to develop fused feature vector on multimodal traits& explore the research work by embedding other biometric traitslike face, fingerprint,Iris, handwritten signature with voice, etc tocreate robust, secure multifactor authentication and biometric identification system and develop an optimized algorithm, an efficient biometric multimodal system based on the high confidence level of accuracy so that signature verificationof bankcustomer in offline mode can be delivered including other areas like airports, cross border, etc.

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Annexure 15.4

Submission Date	Submission Id	Word Count	Character Count
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Reviewers Memorandum

Reviewer's Comment 1: The suggested model for training and testing is based on the Resnet-50 architecture, which was created and tested using 250 samples from each subject. While using the fusion method to create the fused feature vector, the serial fusion algorithm is utilised to concatenate crucial features (Fm).

Reviewer's Comment 2: The study recognises that the main drawback of machine learning approach is the sensitivity of the training data and parameter relationships, as modifications to the training data may result in the production of unexpected results. There is still continuing research on the concatenation of four distinct traits—face, fingerprint, iris, and handwritten signature—in a deep learning context.

Reviewer's Comment 3: The study is very well executed, trials have shown that handwritten signatures have the highest technical viability when combined with facial, fingerprint, and iris attributes. Also, it offers a number of references so that readers can get more in-depth information about the subject.

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Conflict of Interest: Author of a Paper had no conflict neither financially nor academically.

Editorial Excerpt

The article has 0% of plagiarism which is the accepted percentage as per the norms and standards of the journal for publication. As per the editorial board's observations and blind reviewers' remarks the paper had some minor revisions which were communicated on a timely basis to the authors (Dharmendra, Sudhansh and Mangala), and accordingly, all the corrections had been incorporated as and when directed and required to do so. The comments related to this manuscript are noticeably related to the theme **"Unimodal biometric identification system on Resnet-50 residual block in deep learning environment fused with serial fusion"** both subject-wise and research-wise. Even today, a frequent practise in the banking industry is for the desk officer at the counter to manually match the customer's face with their handwritten signature by comparing it to the customer's photo and signature that have already been saved in the bank's database repository. The Indian population in rural areas is not very familiar with digital technology, such as digital or e-sign access. After comprehensive reviews and the editorial board's remarks, the manuscript has been categorized and decided to publish under the "**Empirical Research Paper**" category.

Acknowledgement

The acknowledgment section is an essential part of all academic research papers. It provides appropriate recognition to all contributors for their hard work and effort taken while writing a paper. The data presented and analyzed in this paper by (Dharmendra, Sudhansh and Mangala) were collected first handily and wherever it has been taken the proper acknowledgment and endorsement depicts. The authors are highly indebted to others who facilitated accomplishing the research. Last but not least, endorse all reviewers and editors of GJEIS in publishing in the present issue.

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