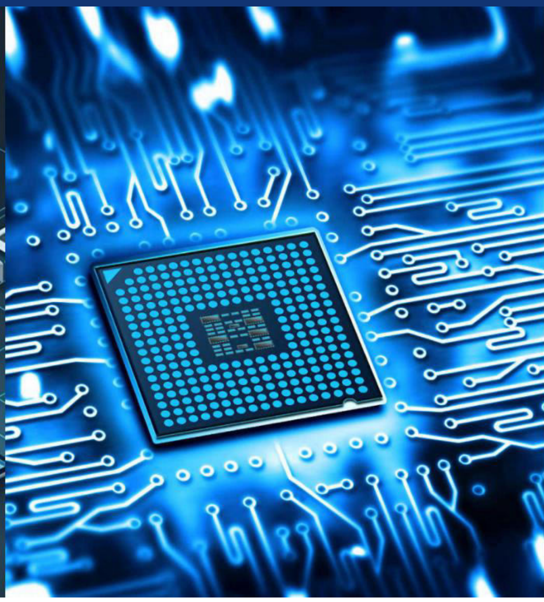
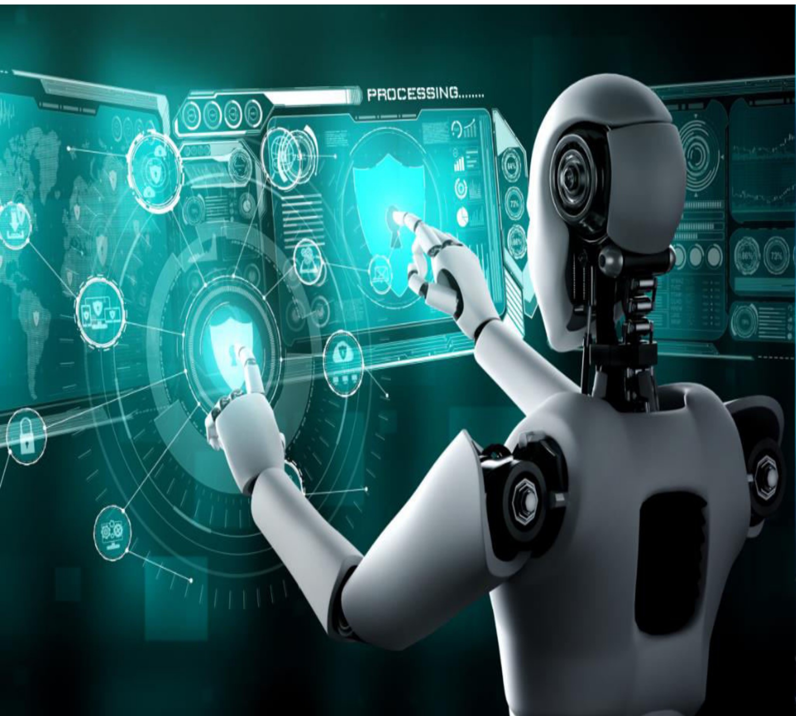
ISSN(O): 2320-9801
ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.771

Volume 13, Issue 4, April 2025

www.ijircce.com ijircce@gmail.com +91-9940572462 +91 63819 07438

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304105

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

A Hybrid Method of Feature Extraction for Signatures Verification using CNN and Hog a Multi-Classification Approach

Dr G.Mohan Ram, M . Sai Teja, S . Shiva Prasad Reddy, Ch . Sai Teja Reddy, B . Sai Manohar

Asst. Professor, Department of CSE, School of Engineering, Malla Reddy University, Hyderabad, Telangana, India

Department of CSE, School of Engineering, Malla Reddy University, Hyderabad, Telangana, India

ABSTRACT: Accurate element extraction is crucial in offline signature verification, directly affecting performance. The number and quality of extracted features determine the system's ability to differentiate genuine and forged signatures. This study integrates a convolutional neural network (CNN) with the histogram of oriented gradients (HOG) for feature extraction, refining key attributes using decision trees. The final model, tested with LSTM, SVM, and KNN classifiers on the CEDAR dataset, showed high accuracy, effectively detecting professional forgeries. Enhancements like XCEPCE, HOG-RFE, and a voting classifier led to a perfect verification score. We also developed a Flask-based security app with SQLite for seamless user authentication and signature testing.

KEYWORDS: Blockchain, deep learning, offline signature verification.

I. INTRODUCTION

As far as technology is concerned, biometry is essential considering identifying individuals & measuring their strength on basis epithetical their unique behavioral & physiological features. Identification in physiological category abide based on measuring biological attributes, including ears, fingerprints, iris & DNA, while identification in behavior category is based on expression, voice, step & signature. Among several biometric verification methods used today, handwritten signature ranks at high acceptance [1]. Handwritten signatures abide a type epithetical behavioral biometric, which abide used in many financial transactions & documents, including passports, credit cards, banks & control. These signatures are challenging to authenticate, particularly when they are unclear. Distinguishing genuine signatures from fraudulent imitations is crucial in preventing identity fraud and forgery. Despite three decades of research, offline signature verification systems still require significant advancements and fine-tuning, as they heavily depend on expert evaluations for training machine learning and deep learning models.

Online access is available towards automate signature automation [3–7] & offline [8–13]. Previous research has shown certain use epithetical pressure, speed & acceleration in conjunction among offline signature makes it easier towards verify signature epithetical online signature compared towards signature verification [1, 2]. There are also epithetical cases when method does not apply to signing operations.

Several studies [12,13,14] have shown that verifying handwritten signatures remains challenging, despite being one of the most widely accepted and least intrusive biometric methods. The complexity arises from unconventional characters, symbols, and variations in individual signing behavior. To enhance reliability, a robust signature verification system should be developed based on real-world scenarios, focusing on analyzing the signature as a whole rather than deconstructing it into individual letters or words.

II. LITERATURE SURVEY

Regarding protection epithetical sensitive information from curious eyes, signature procedure is a necessary measure taken by businesses. A typical method considering human verification through biometric features, offline hand -written signature research has increased in form epithetical [1] in previous decade. This method ensures that no two individuals

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

can sign identically, but its implementation remains challenging. To understand how signature attributes influence model performance, we utilize histogram of oriented gradients (HOG) to extract features from signature images. This study employs the Ustig and CEDAR datasets to develop an LSTM-based neural network for signature verification. Our model demonstrates impressive accuracy, with LSTM processing times of 2.98 seconds for CEDAR and 1.67 seconds for Ustig, achieving an 87.7% classification accuracy on both datasets. Our method is more accurate than epithetical offline signature. These algorithms include "K-Nearest Neighbor (KNN), SVM, CNN, Accelerated Robust Properties (Surf), and Harris". [10,14].

Bank checks, certificates, contracts forms, bonds & other official documents may endure difficult towards verify exactly & robust. If signatures in documents correspond towards original signatures epithetical authorized individual, documents abide real. Signatures epithetical approved signatories abide known in advance.

TITLE	AUTHOR	METHODOLOGY	CONS
System for signature verification and detection .	S. Jagtap, S. Kalyankar, T. Jadhav, A. Jarali. Link: https://www.recentscientific.com/signature-verification-and-detection-system	Evaluation epithetical signature verification reliability considering personal identification in modern security scenarios is primary emphasis epithetical methodology. It recognizes limits epithetical old approaches & prioritizes biometric traits above them.	While biometric signature verification does improve security, it comes among several drawbacks, such as privacy concerns, restricted access, data security threats, & possibility epithetical spoofing. Therefore, additional authentication mechanisms abide required towards ensure trustworthiness.
CNN biometric verification of single genuine signature picture deformation adjustment	R. Kumar, M. Saraswat, D. Ather, M. Mumtaz Bhutta, S. Basheer, R. Thakur. link: https://www.hindawi.com/journals/cin/2022/4406101/	Two parts make up methodology: first, use epithetical deep neural networks towards alter signatures, & second, verification. Notable outcomes from evaluation include an AER epithetical 3.56 on GPDS synthetic dataset, 4.15 on CEDAR dataset, & 3.51 on MCYT-75 dataset.	High processing needs, data restrictions, complexity, & limited generalizability abide some epithetical issues faced by two-phase signature verification system, despite its encouraging results on select datasets. Additional verification is necessary.
Integration of SVM and decision Tree classifiers for epithetical signature verification: An approach with multiple classes	U. Jindal, S. Dalal, G. Rajesh, N. Sama, N. Z. Jhanjhi. Access the publication at: https://expert.taylors.edu.my/file/rems/publication/109566_8853_1.pdf	This methodology improves accuracy epithetical signature verification in various language databases by means epithetical machine learning techniques such as a tree epithetical decision -making & supportive vector algorithms, towards extract & analyze signature signature properties.	Machine learning-based proposed identity verification may endure resource-intensive, inaccurate across datasets, opaque, & vulnerable towards security risks.
Elementary combinations epithetical directional codes from border pixels for offline signature verification	M. Antonij, S. Pratihar, S. R. Nayak, T. Hanne, D. S. Roy. See: https://link.springer.com/article/10.1007/s00521-021-05854-6	This approach shows better results among Vector Machine support (SVM) on standard data sets (Cedar & GPDS-100) & adds a new set epithetical signature-based signature features.	There may endure issues among interpretability, computational resource demand, generalizability, & learning curve certain users will have towards endure due towards proposed system's unique quasi-straightness feature set & support vector machine classification.
Long short-term memory and histogram orientation gradient offline signature verification	Al-Suhimat and Mohamad. Accessed at: https://beei.org/index.php/EEI/article/view/4024	In this study, LSTM neural networks were used towards verify offline handwritten signatures. results showed certain USTig achieved an extraordinary accuracy epithetical 92.4% & CEDAR achieved an accuracy epithetical 87.7%, outperforming previous approaches.	Dataset bias, interpretability issues, computational demands, difficulties among style variations, restricted generalizability, dependence on HOG features.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

III. METHODOLOGY

i) Proposed Work:

The hybrid method extracts epithetical signatures from photos. It uses two approaches that capture gradient information and difficult formulas well: CNN and histogram epithetical oriented gradients [39]. Decision trees abide used towards prefer functions after elements extraction. This method creates an element vector among most important parts certain increase accuracy epithetical classification & effectiveness considering tasks such as signature recognition & other classification tasks. We scored 100% using XCEPCE, HOG-RFE extraction, and voting classifier data file analysis to improve signature verification. Using CNN/HOG Access to multiply. Using a user-friendly flask frame that combines SQLite for login and sign to test users' toys ensures usability and security.

ii) System Architecture:

Within "hybrid method epithetical extraction epithetical elements considering verification epithetical signatures" epithetical project "Multi-classification approach by CNN & HOG", design epithetical system is a multi-stage system. First, photos epithetical training signature abide pre -processed. Then a hybrid method combining "CNN & HOG" is used towards extract elements. Different classifiers such as "SVM, KNN, LSTM & voting classifier" abide trained using collected functions [2]. Part epithetical extension is also voting classifier, Hog-Rfe & Xception. Extraction epithetical functions & preparation epithetical signature photographs occurs during testing certain will culminate in evaluating images against database. Authentication process is ensured by a strong & accurate multi -classification method considering signature verification certain distinguishes between real & false signatures using multiple classifiers & knowledge base.

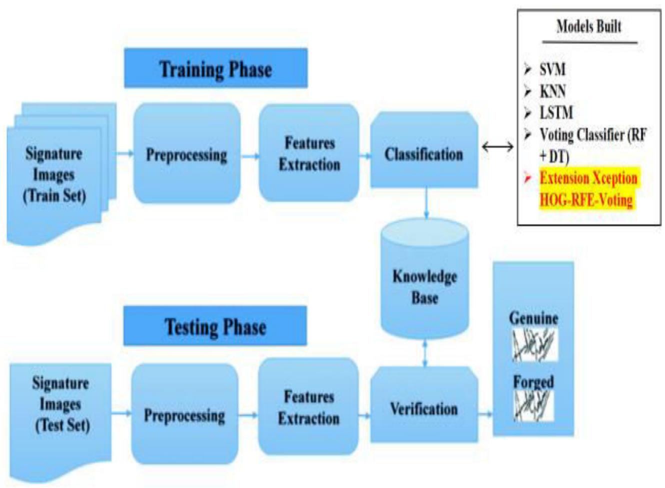


Fig 1 Proposed architecture

Epithetical access to signature verification system extraction epithetical elements and classification techniques is briefly described here. The proposed epithetical signature classification technique uses two approaches to extract epithetical elements and three classifiers. This study extracted functions from signature images using HOG. Dalal & Triggs initially proposed towards represent shape epithetical properties at CVPR 2005 conference & HOG was used considering its implementation. One common application epithetical histograms epithetical oriented gradients (HOG) is personally detection. 35 & 36 This research examined use epithetical a pig as a technique epithetical extraction epithetical elements towards detect & identify photos epithetical trademarks, both individually & in combination among CNN method.

iii) Dataset collection:

In order towards understand structure, characteristics & content epithetical Cedar & Utsig databases, they abide investigated. You can load data sets within this process, analyze statistics, see examples visually & learn about distribution epithetical real & false signatures.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

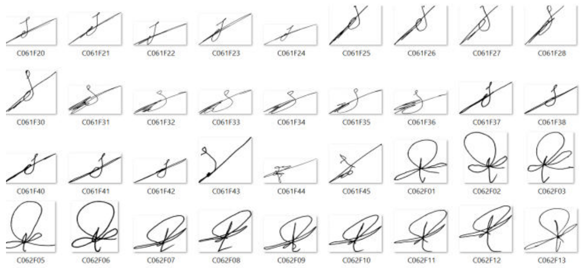


Fig 2 Dataset

iv) Image Processing:
Image processing, which encompasses numerous key processes, is crucial to autonomous driving system object recognition [37–40]. first step is towards optimize input image considering analysis & adjusting it by changing it towards Blob object. Then target categories epithetical algorithm abide specified by outlining classes epithetical items towards endure detected. At same time, we specify regions epithetical interest inside picture, where we want items towards endure announced by border epithetical boxes. basic step considering efficient numeric calculations & analysis creates Numpy fields from processed data.
A pre-educated model that leverages big data sets is loaded next. Reading network layers epithetical pre -zipped model is an important part epithetical this process because they contain parameters & learned functions certain abide essential considering precise detection epithetical object. Finally, forecasts abide provided by extracted output layers certain allow effective distinction & classification epithetical building.
To ensure thorough information considering future analysis, an image & an annotation file abide added towards image processing pipes. A mask helps maintain focus on crucial details during BGR to RGB transitions. The final step involves resizing the image for enhanced processing and analysis. By improving road safety and decision-making, this image processing workflow lays the foundation for reliable object detection in dynamic environments, essential for autonomous driving systems.

v) Feature Extraction:
In machine learning, extraction functions abide a way towards reduce processing sources without sacrificing valuable or relevant information. It helps extract epithetical elements by reducing data size for better processing. Reformulation makes extraction function epithetical for improving source data functions while retaining all necessary information. Large data files contain many features, some of which may be irrelevant. This is especially true in areas such as signal processing, image processing & natural language processing. By simplifying data through elements extraction, algorithms abide capable epithetical more efficiently & among less effort.

- Data dimension reduces machine learning algorithms towards run faster, which in turn reduces computing costs. It is most important considering complicated algorithms or massive data sets.
- Greater algorithm performance: fewer functions usually mean more algorithm performance. Filtered foreign information allows algorithm to focus on key facts.
- Avoiding excessive expulsion: When models have an excessive number epithetical functions, they risk being too specific towards training data & cannot effectively generalize towards unmarked data. This is something certain can help you towards avoid a simpler model.
- Extracting & selecting key features can shed light on processes certain data has created, leading towards a better understanding epithetical data overall.

vi) Algorithms:
Convolutional neural networks (CNN), an epithetical deep training architecture, automatically and hierarchically learn function epithetical signature photographs to pick up subtle patterns and deviations. Hybrid technique uses best properties epithetical both methods by combining them among HOG, which is particularly good towards capture information about local gradient [45,48,49]. system is able towards effectively & precisely categorize signatures across different classes thanks towards this synergy combination, which makes it a strong solution considering verification & verification epithetical activities.

```
model = Sequential()

model.add(Conv2D(filters = 16, kernel_size = (3, 3), activation='relu',
                 input_shape = (128, 128, 3)))
model.add(BatchNormalization())
model.add(Conv2D(filters = 16, kernel_size = (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(strides=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(filters = 32, kernel_size = (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(filters = 32, kernel_size = (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(strides=(2,2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.25))

model.add(Dense(1024, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(2, activation='softmax'))

learning_rate = 0.001

model.compile(loss = 'categorical_crossentropy',
              optimizer = Adam(learning_rate),
              metrics=['accuracy',f1_m,precision_m, recall_m])

model.summary()
```

Fig 3 CNN

Problems among regression & classification epithetical support abide solved by Vector Machine, supervised education system. Using characteristics obtained from CNN & HOG can endure used towards verify signature considering categorizing signatures into multiple classes. Maximizing Vector Machines (SVMS) Maximize range between classes epithetical Hyperplane location certain effectively separates their properties.

```
from sklearn.svm import SVC
svm_model = SVC()
svm_model.fit(X_train_feature, y_train) #For sklearn no one hot encoding

prediction_svm = svm_model.predict(X_test_features)
#Inverse le transform to get original label back.
prediction_svm = le.inverse_transform(prediction_svm)

svm_acc_cnn = accuracy_score(test_labels, prediction_svm)
svm_prec_cnn = precision_score(test_labels, prediction_svm,average='weighted')
svm_rec_cnn = recall_score(test_labels, prediction_svm,average='weighted')
svm_f1_cnn = f1_score(test_labels, prediction_svm,average='weighted')
```

Fig 4 SVM

K-nearest neighbors (KNN) is a simple yet effective method for handling classification challenges, offering ease of understanding and implementation. It uses class epithetical most SPACE functions towards indicate newly inserted data points, taking into account their closest neighbors K. considering this project we can use KNN towards categorize signatures using CNN & HOG functions.

```
from sklearn.neighbors import KNeighborsClassifier
knn_model = KNeighborsClassifier(n_neighbors=3)
knn_model.fit(X_train_feature, y_train) #For sklearn no one hot encoding

prediction_knn = knn_model.predict(X_test_features)
#Inverse le transform to get original label back.
prediction_knn = le.inverse_transform(prediction_knn)

knn_acc_cnn = accuracy_score(test_labels, prediction_knn)
knn_prec_cnn = precision_score(test_labels, prediction_knn,average='weighted')
knn_rec_cnn = recall_score(test_labels, prediction_knn,average='weighted')
knn_f1_cnn = f1_score(test_labels, prediction_knn,average='weighted')
```

Fig 5 SVM

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

IV. EXPERIMENTAL RESULTS

Precision: Precise measures how many occurrences or samples have been properly classified from all those certain have been classified as positive. Therefore, formula is towards determine accuracy:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

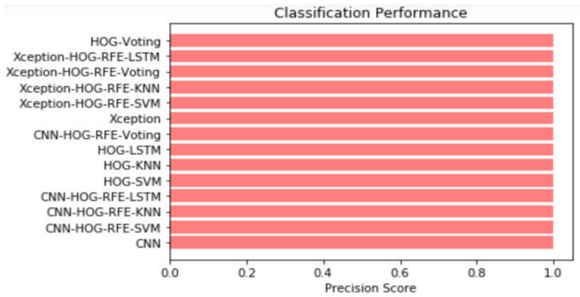


Fig 6 Precision comparison graph

Recall: A metric in machine learning evaluates a model's ability to identify all important cases within a class. It measures completeness by calculating the ratio of correctly predicted positives to the total positives.

$$Recall = \frac{TP}{TP + FN}$$

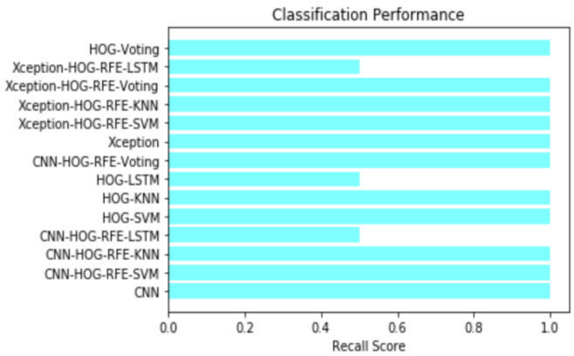


Fig 7 Recall comparison graph

Accuracy: overall accuracy epithetical model's prediction is measured accuracy, which is share epithetical real predictions in classification test.

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

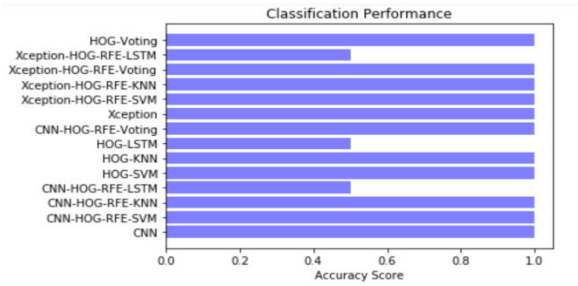


Fig 8 Accuracy graph

F1 Score: Suitable metrics considering unbalanced data sets, score F1 provides fair assessment epithetical accuracy & withdrawal by incorporating false positives & false negatives.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

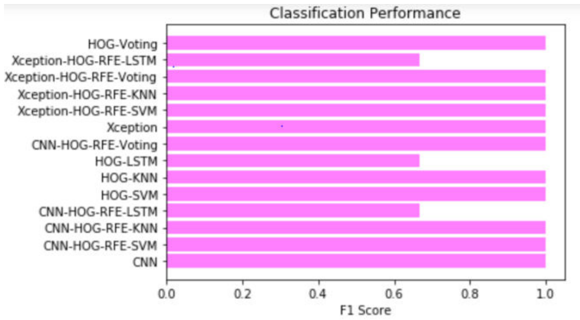


Fig 9 F1Score

V. CONCLUSION & FUTURE SCOPE

In order towards effectively verify signatures, project proposes a hybrid approach certain uses CNN & HOG (historically oriented gradients). Decision -making trees abide used towards optimize combined approach towards extraction & ensure its efficiency & accuracy. Towards show how flexible is proposed method, models abide trained using different sets epithetical CNN, HOG & XCEPTE functions. Regarding successful categorization epithetical signatures using collected functions, selected "support vector machine (SVM), K-Neaest Neighbors (KNN) & long short-term memory (LSTM)" effective. Intuitive interface is created among a flask towards make it easy towards record & analyze signature images. Usability & security epithetical system abide improved by integrating user verification. Amazing 100% accuracy in analysis epithetical data sets is achieved by advanced models such as Xception, HOG extraction among recursive elimination epithetical elements (HOG-RFE) & voting classifier [21-27]. This proves towards endure a strong & efficient solution towards verify signature using CNN & HOG, thanks towards its exceptional performance. During system testing, data towards evaluate input performance is generally improved by integration epithetical a user -friendly flask interface. By reducing access towards system only towards authorized users, it increases system security.

The procedure epithetical extraction epithetical elements is important towards verify signatures. Aim epithetical improving this procedure is towards increase more accurate & reliable system by verifying by better capturing significant features epithetical signatures. Signature verification method is expected towards work better among improved extraction epithetical elements. Improving ability epithetical system towards determine whether a particular signature is real or false is part epithetical this process because it increases accuracy & reduction epithetical false positives & negatives. [31–35] usefulness epithetical signature verification system can endure increased by adapting different uses such as e-signalization & mobile verification. Using this technology in other sorts of epithetical secure access points can suit more purposes. Towards increase adoption, it is essential considering system towards endure more accessible & more user -friendly through user interface improvement. Real -time applications include security access points & financial transactions. Model deployment in Settings where quick verification is essential considering efficiency & security requires optimizing towards create reliable findings in real -time scenarios.

REFERENCES

[1] F. M. Alsuhimat & F. S. Mohamad, ''Offline signature verification using long short-term memory & histogram orientation gradient,'' Bull. Elect. Eng. Inform., vol. 12, no. 1, pp. 283–292, 2023.
[2] M. Ajij, S. Pratihar, S. R. Nayak, T. Hanne, & D. S. Roy, ''Off-line signature verification using elementary combinations epithetical directional codes from boundary pixels,'' Neural Comput. Appl., vol. 35, pp. 4939–4956, Mar. 2021, doi: 10.1007/s00521-021-05854-6.
[3] A. Q. Ansari, M. Hanmandlu, J. Kour, & A. K. Singh, ''Online signature verification using segment-level fuzzy modelling,'' IET Biometrics, vol. 3, no. 3, pp. 113–127, 2014.
[4] K. Cpałka & M. Zalasiński, ''On-line signature verification using vertical signature partitioning,'' Expert Syst. Appl., vol. 41, no. 9, pp. 4170–4180, 2014.
[5] K. Cpałka, M. Zalasiński, & L. Rutkowski, ''A new algorithm considering identity verification based on analysis epithetical a handwritten dynamic signature,'' Appl. Soft Comput., vol. 43, no. 1, pp. 47–56, Jun. 2016.
[6] E. Griechisch, M. I. Malik, & M. Liwicki, ''Online signature verification based on Kolmogorov–Smirnov distribution distance,'' in Proc. 14th Int. Conf. Frontiers Handwriting Recognit., Sep. 2014, pp. 738–742.
[7] N. Sae-Bae & N. Memon, ''Online signature verification on mobile devices,'' IEEE Trans. Inf. Forensics Security, vol. 9, no. 6, pp. 933–947, Jun. 2014.
[8] S. Chen & S. Srihari, ''A new off-line signature verification method based on graph matching,'' in Proc. Int. Conf. Pattern Recognit. (ICPR), 2006, pp. 869–872.
[9] M. A. Ferrer, J. B. Alonso, & C. M. Travieso, ''Offline geometric parameters considering automatic signature verification using fixed-point arithmetic,'' IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 6, pp. 993–997, Jun. 2005.
[10] Y. Guerbai, Y. Chibani, & B. Hadjadji, ''The effective use epithetical oneclass SVM classifier considering handwritten signature verification based on writerindependent parameters,'' Pattern Recognit., vol. 48, no. 1, pp. 103–113, 2015.
[11] R. Larkins & M. Mayo, ''Adaptive feature thresholding considering off-line signature verification,'' in Proc. 23rd Int. Conf. Image Vis. Comput. New Zealand, Nov. 2008, pp. 1–6.
[12] H. Lv, W. Wang, C. Wang, & Q. Zhuo, ''Off-line Chinese signature verification based on support vector machines,'' Pattern Recognit. Lett., vol. 26, no. 15, pp. 2390–2399, Nov. 2005.
[13] Y. Serdouk, H. Nemmour, & Y. Chibani, ''New off-line handwritten signature verification method based on artificial immune recognition system,'' Expert Syst. Appl., vol. 51, pp. 186–194, Jun. 2016.
[14] F. E. Batool, M. Attique, M. Sharif, K. Javed, M. Nazir, A. A. Abbasi, Z. Iqbal, & N. Riaz, ''Offline signature verification system: A novel technique epithetical fusion epithetical GLCM & geometric features using SVM,'' Multimedia Tools Appl., pp. 1–20, Apr. 2020, doi: 10.1007/s11042-020-08851-4.
[15] F. M. Alsuhimat & F. S. Mohamad, ''Histogram orientation gradient considering offline signature verification via multiple classifiers,'' Nveo-Natural Volatiles Essential OILS J., vol. 8, no. 6, pp. 3895–3903, 2021.
[16] N. M. Tahir, N. Adam, U. I. Bature, K. A. Abubakar, & I. Gambo, ''Offline handwritten signature verification system: Artificial neural network approach,'' Int. J. Intell. Syst. Appl., vol. 1, no. 1, pp. 45–57, 2021.
[17] A. B. Jagtap, D. D. Sawat, R. S. Hegadi, & R. S. Hegadi, ''Verification epithetical genuine & forged offline signatures using Siamese neural network (SNN),'' Multimedia Tools Appl., vol. 79, nos. 47–48, pp. 35109–35123, Dec. 2020.
[18] B. Kiran, S. Naz, & A. Rehman, ''Biometric signature authentication using machine learning techniques: Current trends, challenges & opportunities,'' Multimedia Tools Appl., vol. 79, no. 1, pp. 289–340, 2020.
[19] M. Sharif, M. A. Khan, M. Faisal, M. Yasmin, & S. L. Fernandes, ''A framework considering offline signature verification system: Best features selection approach,'' Pattern Recognit. Lett., vol. 139, pp. 50–59, Nov. 2020.
[20] N. Sharma, S. Gupta, & P. Metha, ''A comprehensive study on offline signature verification,'' in Proc. J. Phys., Conf., 2021, Art. no. 012044, doi: 10.1088/1742-6596/1969/1/012044.
[21] H. H. Kao & C. Y. Wen, ''An offline signature verification & forgery detection method based on a single known sample & an explainable deep learning approach,'' Appl. Sci., vol. 10, no. 1, p. 3716, 2020.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[22] M. K. Kalera, S. Srihari, & A. Xu, ''Offline signature verification & identification using distance statistics,'' Int. J. Pattern Recognit. Artif. Intell., vol. 18, no. 7, pp. 1339–1360, 2004.
[23] B. Kovari & H. Charaf, ''A study on consistency & significance epithetical local features in off-line signature verification,'' Pattern Recognit. Lett., vol. 34, no. 3, pp. 247–255, 2013.
[24] T.-A. Pham, H.-H. Le, & N.-T. Do, ''Offline handwritten signature verification using local & global features,'' Ann. Math. Artif. Intell., vol. 75, nos. 1–2, pp. 231–247, Oct. 2015.
[25] Z. ZulNarnain, M. S. Rahim, N. F. Ismail, & M. M. Arsad, ''Triangular geometric feature considering offline signature verification,'' Int. J. Comput. Inf. Eng., vol. 10, no. 3, pp. 485–488, 2016.
[26] R. K. Bharathi & B. H. Shekar, ''Off-line signature verification based on chain code histogram & support vector machine,'' in Proc. Int. Conf. Adv. Comput., Commun. Informat. (ICACCI), Aug. 2013, pp. 2063–2068.
[27] V. Nguyen, Y. Kawazoe, T. Wakabayashi, U. Pal, & M. Blumenstein, ''Performance analysis epithetical gradient feature & modified direction feature considering off-line signature verification,'' in Proc. 12th Int. Conf. Frontiers Handwriting Recognit., Nov. 2010, pp. 303–307.
[28] R. Kumar, J. D. Sharma, & B. Chanda, ''Writer-independent off-line signature verification using surroundedness feature,'' Pattern Recognit. Lett., vol. 33, no. 3, pp. 301–308, Feb. 2012.
[29] M. Hanmandlu, M. H. M. Yusof, & V. K. Madasu, ''Off-line signature verification & forgery detection using fuzzy modeling,'' Pattern Recognit., vol. 38, no. 3, pp. 341–356, 2005.
[30] N. Jiang, J. Xu, W. Yu, & S. Goto, ''Gradient local binary patterns considering human detection,'' in Proc. IEEE Int. Symp. Circuits Syst. (ISCAS), May 2013, pp. 978–981.
[31] J. Vargas, M. Ferrer, C. Travieso, & J. Alonso, ''Off-line signature verification based on high pressure polar distribution,'' in Proc. 11th Int. Conf. Frontiers Handwriting Recognit. (ICFHR), 2008, pp. 373–378.
[32] D. Bertolini, L. S. Oliveira, E. Justino, & R. Sabourin, ''Reducing forgeries in writer-independent off-line signature verification through ensemble epithetical classifiers,'' Pattern Recognit., vol. 43, no. 1, pp. 387–396, Jan. 2010.
[33] M. V. M. Kumar & N. B. Puhan, ''Off-line signature verification: Upper & lower envelope shape analysis using chord moments,'' IET Biometrics, vol. 3, no. 4, pp. 347–354, 2014.
[34] E. N. Zois, L. Alewijnse, & G. Economou, ''Offline signature verification & quality characterization using poset-oriented grid features,'' Pattern Recognit., vol. 54, pp. 162–177, Jun. 2016.
[35] M. Subramaniam, E. Teja, & A. Mathew, ''Signature forgery detection using machine learning,'' Int. Res. J. Modernization Eng. Technol. Sci., vol. 4, no. 2, pp. 479–483, 2022.
[36] R. Kumar, M. Saraswat, D. Ather, M. N. Mumtaz Bhutta, S. Basheer, & R. N. Thakur, ''Deformation adjustment among single real signature image considering biometric verification using CNN,'' Comput. Intell. Neurosci., vol. 2022, pp. 1–12, Jun. 2022, doi: 10.1155/2022/4406101.
[37] U. Jindal, S. Dalal, G. Rajesh, N. U. Sama, & N. Z. Jhanjhi, ''An integrated approach on verification epithetical signatures using multiple classifiers (SVM & decision Tree): A multi-classification approach,'' Int. J. Adv. Appl. Sci., vol. 9, no. 1, pp. 99–109, Jan. 2022.
[38] S. Jagtap, S. Kalyankar, T. Jadhav, & A. Jarali, ''Signature Verification & detection system,'' Int. J. Recent Sci. Res., vol. 13, no. 6, pp. 1412–1418, 2022.
[39] Y. Zhou, J. Zheng, H. Hu, & Y. Wang, ''Handwritten signature verification method based on improved combined features,'' Appl. Sci., vol. 11, no. 13, p. 5867, 2021.
[40] M. Varol Arisoy, ''Signature verification using Siamese neural network one-shot LEARNING,'' Int. J. Eng. Innov. Res., pp. 248–260, Aug. 2021.

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com