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An Explainable Hybrid Artificial Intelligence Approach for Robust Image Forgery Detection and Authentication Using Cognitive Image Authenticity Intelligence Engine

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Abstract : An image manipulation develop rapidly and AI-based tools become popular among image editors allowing manipulations of high complexity and posing risks to digital forensics, journalism investigation, medicine and cyber security, the problem of image forgery detection becomes increasingly important. At present, the algorithms used in the field of image forgery detection and authentication sufferfrom the following shortcomings.It was designed to detect particular type of image manipulations, have poor generalizability to heterogeneous data sets, require significant computing resources and do not provide for explain ability of decisions made. To achieve, this research proposes to apply the concept of Cognitive Image Authenticity Intelligence Engine (CIAIE) an explainable hybrid artificial intelligence algorithm designed for the image forgery detection and authentication. The proposed algorithm utilizes such technologies as Principal Component Analysis (PCA), Conventional Neural Network (CNN), Vision Transformer (ViT), U-Net, Extreme Gradient Boosting (XGBoost), and Explainable AI (XAI) for dimensionality reduction, feature extraction, forgery localization, authenticity classification and decision making. The experimental evaluation carried out in Python showed the superior performance of the proposed approach with the accuracy of 94.68%. The proposed method was capable of achieving accurate, interpretable, and computationally efficient real-time image authentication, making it appropriate for many digital forensic and cyber security purposes.
Keywords: Digital Forensics, Explainable Intelligence, Image Authentication, Image Forgery Detection, Intelligent Vision, Real-Time Verification

I. INTRODUCTION

The process of image forgery is growing increasingly sophisticated because of rapid advances in image manipulation tools and artificial intelligence-based forgery methods. Sophisticated intelligent authentication techniques capable of identifying manipulative actions like copy-move, splicing, in painting, retouching, and AI forgery while being robust, reliable, explaining their work and having real-time forensic verification capabilities should be developed for various digital environments. There are several weaknesses of current approaches used in detection of image forgery: the focus on certain type of manipulations; consumption of a lot of computing power; weak generalization capabilities in different data sets; inability to provide explanation for their conclusions; inability to work with advanced AI forgeries. Also, localization capabilities and robustness in adversarial situations with manipulations are additional problems in the area.

Vision Transformer and SVM gave improved robustness against adversarial attacks and better classification results together [1]. Hybrid CNN-Transformer gave accurate localization of forgery thanks to complementary local and global features [2]. Sequence-to-sequence Transformer allowed for effective detection and localization of copy-move forgeries by means of modeling long-range dependencies between features [3]. Hierarchical representation driven by language allowed for better localization of forgery and understanding of manipulated image regions semantically [4].Multi-scale edge guided self-supervised learning increased the effectiveness of forgery detection since it ensured consistency of manipulation boundaries and context [6]. The uncertainty guided refinement was able to detect the presence of scientific image splicing due to the higher localization accuracy and detection performance [7]. The combination of error level analysis and CNN aided in verification of images by virtue of the forensic feature extraction method [8]. The siamese network architecture assisted in effective forgery detection through learning of discriminative similarity between regions of an image [9]. Deep learning made use of error level and noise residual analysis in the detection of image manipulation artifacts [10]. Hybrid optimization technique helped in detection of forgery in compressed images while preserving localization accuracy regardless of low image quality [11]. Feature pyramid learning helped in detecting image in painting forgeries through multi-scale semantic feature extraction [12]. Enhanced Mask Region CNN detected blind image forgeries through region-based convolutional feature extraction [13]. End-to-end attention learning improved forgery localization through emphasis on regions of image manipulation and ignoring other irrelevant parts of background information [14]. CAMU-Net applied coordinate attention and multi-scale up sampling in the localization and segmentation of copy move forgeries [15]. The proposed Cognitive Image Authenticity Intelligence Engine(CIAIE) techniques will exploiting the abilities of PCA, CNN, Vision Transformer, U-Net, XG Boost, and XAI to enhance feature representation, forgery localization, classification accuracy, computational speed, and the explanations provided for decisions made by the system. The integration of this new architecture will help in forgery detection using different forgery types and enhanced robustness while reducing false positives.

The main contributions and motivations of this research are as follows

- Conceived the Cognitive Image Authenticity Intelligence Engine (CIAIE) using PCA, CNN, Vision Transformer, U-Net, XGBoost, and XAI.
- Localizes forgery in images and classifies the forgery based on local and global information using CNNs, transformers, segmentation, and ensembles of intelligent systems.
- Increase in interpretation and trust of the users through the utilization of the Explainable AI technique in order to provide visual proof and justification of the image forgery determination.
- A computationally efficient algorithm for detecting forgeries that can successfully detect copy-move, splicing, in painting, retouching, and AI-based forgeries.

Organization: The remainder of the research is organized as follows. Section II discusses briefly the existing works on the topic. In section III, our proposed CIAIE method is discussed. In section IV, the results obtained through experiments are presented. In section V, conclusions are drawn.

II. BACKGROUND STUDY

- M.Abdel maksoud et al. (2025) [1] proposed Hybrid Vision Transformer-SVM forgery detection adversarial robustness was improved, the method lacked explain ability, forgery detection accuracy was enhanced.
- S.Sharma et al. (2025) [2] proposed an adversarial robustness in CNN-Transformer localization hybrid feature learning was efficient in localization. Computation cost remained relatively high, robustness was improved.
- G.Hao et al. (2025) [3] proposed a sequence-to-sequence Transformer for copy-move detection localization was improved.generalized forgery detection was weak, detection accuracy was improved.
- X.Guo et al. (2024) [4] proposed a Language-guided hierarchical localization semantic reasoning was improved in forgery detection, computational overhead was observed, localization performance was improved considerably.
- Q.Li et al. (2024) [5] proposed a Hierarchical U-Net segmentation was utilized by forgery region localization was improved, explainable decision support was lacking, segmentation accuracy was improved.
- L.Zhang et al. (2024) [6] proposed an Edge-guided self-supervised learning was applied by manipulation boundaries were improved detection of AI-generated forgeries was hard, detection robustness was improved.
- H.Li et al. (2024) [7] proposed a scientific image splicing was detected using uncertainty refinement, localization was improved, other forgery types were not considered, reliability was improved.
- Mohamed & Hassan (2024) [8] proposed an Error Level Analysis and CNN were used by authenticity verification performance was improved, poor representation of context was observed; improved classification accuracy.
- E.Ramirez-Rodriguez et al. (2024) [9] proposed an image splicing using Siamese networks was proposed by improvement in similarity learning was seen, diversity of forged images adaptability was not sufficient, detection accuracy improved.
- Y.Jiang et al (2024) [10] proposed a combination of deep learning, error levels, and noise residuals was performed by detection accuracy of tampering improved, lack of explain ability was seen, robustness improved.
- Bhowal et al (2024) [11] proposed a forgery detection using hybrid optimization was proposed by compressed images forgery detection improved, more effective computations were needed, localization accuracy improved.
- S.Aly et al (2025) [12] proposed an in painting detection using feature pyramid learning, multi scale features were improved, poor ability of general forgery detection was observed.

- V.S.Tallapragada et al (2024) [13] proposed a blind forgery localization using enhanced Mask R-CNN was implemented by explainable interpretation was not enough, improved detection accuracy was seen.
- Y.He et al (2025) [14] proposed anAttention Localization was introduced by Attention was localized successfully, high cost of computation remained, localization precision increased.
- K.Zhao et al (2024) [15] proposed a CAMU-Netutilize coordinate attention, the copy-move localization task got improved, the multiple forgery generalization capability remained weak, the segmentation precision was enhanced.

III. PROPOSED METHODOLOGY

Methodology introduced in the research introduces the concept of Cognitive Image Authenticity Intelligence Engine (CIAIE), which will be used to detect and authenticate image forgery. Methodology includes preparation of the dataset, image pre-processing and representation of features, intelligent visual analysis, forgery localization, authenticity verification, decision generation process and learning process. Mathematical formulas and algorithms are developed to represent each step of the process accurately, which allows for reliable detection of various image manipulations techniques in real-time and ensures high-performance authentication.

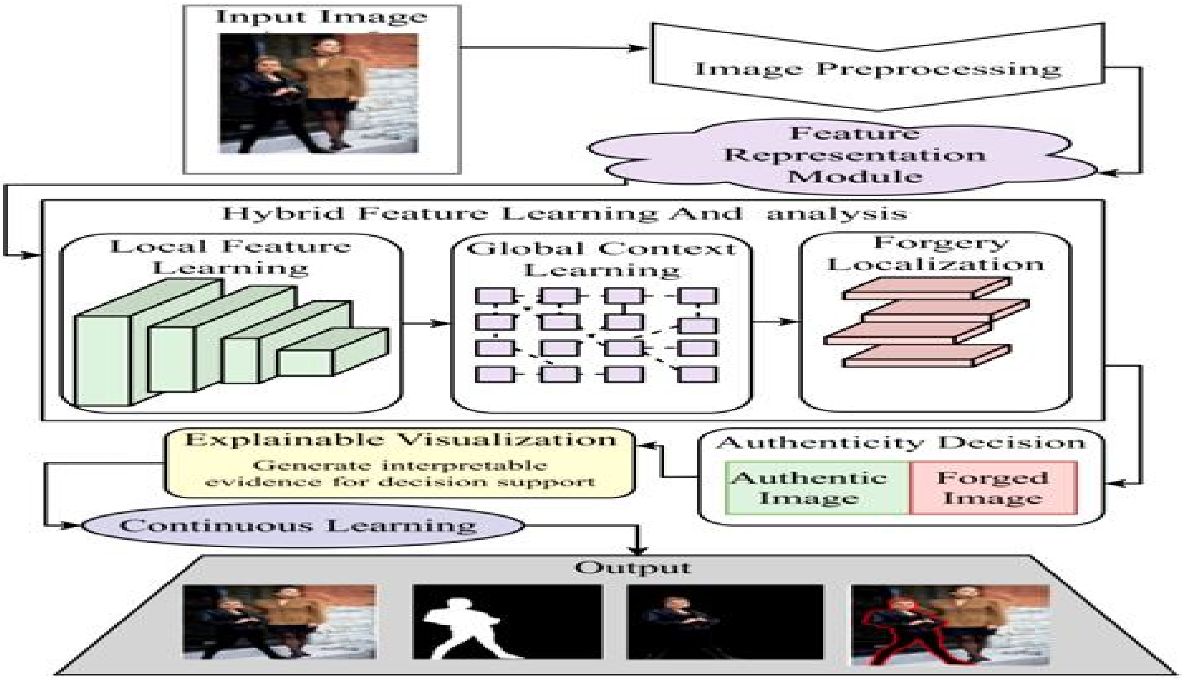

Fig 1. Systematic Architecture of the Proposed Cognitive Image Authenticity Intelligence Engine (CIAIE)

The Fig.1 depicts the entire CIAIE process which involves image acquisition, pre-processing, feature extraction, visual feature learning, forgery localization, interpretation visualization, authenticity prediction, and continual learning processes. This architecture produces forgery localization masks, interpretable authentication reports, and real-time image authenticity validation.

A. Dataset Description

The CASIA 2.0 Image Tampering Detection Dataset https://www.kaggle.com/datasets/divg07/casia-20-image-tampering-detection-dataset has been used to evaluate the proposed model for image forgery detection. The dataset contains 12,614 colored images, out of which 7,491 are authentic images while 5,123 are tampered images through the process of copy-move and splicing forgery. Different resolutions and formats of images make sure that various scenarios of forgery exist in the dataset, thereby making the dataset ideal for training and testing of image authenticity verification models.

B. Proposed Algorithm

The Cognitive Image Authenticity Intelligence Engine (CIAIE) is an Explainable Artificial Intelligence (Explainable AI) algorithm that usethe following algorithms in order to perform image forgery detection and image authentication: PCA, CNN, Vision Transformer, U-Net, Extreme Gradient Boosting, and Explainable AI. PCA reduces the redundant features from images, while CNN and Vision Transformer capture the local and global representations from images. U-Net is used for localization of forgery and XG Boost for accurate classification.

C. Intelligent Forgery Verification and Forgery Detection

This section explains how intelligent forgery verification takes place by the use of forgery identification and accurate localization of the forged areas within images. Pre-processing, feature representation, forgery authentication, forgery detection and forgery localization are some of the processes that are carried out to achieve the objective of accurate detection of copy move, splicing, in painting, retouching, and artificial forgery.

$$I_n(x, y) = \frac{I(x,y) - I_{min}}{I_{max} - I_{min}} \qquad (1)$$

Equation (1) was used to normalize the image before feature extraction in order to remove variations in lighting conditions and improve learning stability.

$I(x, y)$ denotes original intensity value I_{min} and I_{max} are the minimum and maximum intensity values respectively while $I_n(x, y)$ is the normalized image.

$$Z = XW \quad (2)$$

Equation (2) was used to reduce dimensions and retain critical information in the image. X indicates feature vector matrix, W represents eigenvector projection matrix, w_i denotes principal components and Z is dimensionally reduced feature representation.

$$F = \sigma(W_c * Z + b_c) \quad (3)$$

In equation (3) extracting local texture and edge information of the down-sampled images, equation (3) was utilized according to this expression: Z is the output of PCA process, W_c is the convolutional kernel, $*$ is the operator, b_c is the bias of convolutional kernel, σ is the activation function, and F is the feature map.

$$A = \mathrm{Softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \quad (4)$$

In equation (4) Long-term contextual dependencies, which are necessary for detection of image manipulation. There, Q, K, and V are matrices for query, key, and value correspondingly, moreover d is the dimensionality of feature.

D. Explainable Decision Intelligence for Real-Time Forgery Analysis

In this section, explainable decision intelligence is applied to ensure interpretation of authenticity scores and visualization of regions where images are manipulated. Real-time analysis, continual learning, scalability, robustness against novel forgery techniques, and security of application in digital forensics, cyber security, journalism, health care, and investigation is provided here.

$$M = \sigma(W_u F + b_u) \quad (5)$$

In equation (5) acquiring forgery localization masks, was utilized in the form of the following expression: There, F is an extracted feature map, W_u are segmentation weights, b_u is the bias of segmentation layer, σ is the sigmoid activation function, and M is the forgery localization mask.

$$\hat{y} = \sum_{i=1}^{K} f_i\,(F) \quad (6)$$

The equation (6) was used for image authenticity classification with ensemble learning method. Here, F stands for hybrid extracted features, f_i is the i^{th}decision tree, K stands for number of decision trees, and $\hat{y}$ is predicted authenticity score. Equation (6) enhances the accuracy of classification process.

$$E_i = \frac{|S_i|}{\sum_{j=1}^{n}|S_j|} \quad (7)$$

The equation (7) was used to determine normalized feature importance for decision intelligence interpretability purposes. Here, S_i is importance score of feature i, n is number of extracted features, and E_i is normalized feature importance score.

$$D = \begin{cases} 1, & \hat{y} \geq \tau \\ 0, & \hat{y} < \tau \end{cases} \quad (8)$$

The equation (8) determined final authenticity decision based on confidence existing 1 of classification process. In this case, $\hat{y}$is the predicted probability of authenticity, τ is the decision threshold, D = 1 represents forgery, and D = 0 represents authentic images.

Algorithm: Cognitive Image Authenticity Intelligence Engine

Input:
D = {I1, I2, …, IN} : Image forgery dataset
It : Real-time input image
Begin
1. Acquire image dataset and real-time image.
2. Preprocess images (denoising, normalization, resizing, enhancement).
3. For each image Ii do
Zi ← PCA(Ii)
Fi ← CNN(Zi)
Ai ← VisionTransformer(Fi)
Mi ← UNet(Ai)
Yi ← XGBoost(Mi)
Ei ← Explainability(Yi)
End For
4. Train model:
L = Loss (Ytrue, Yi)
$\theta \leftarrow \theta - \eta\nabla L$
5. While new image It arrives do
Preprocess(It)
$\hat{Y}$t ← XGBoost (UNet (VisionTransformer(CNN(PCA(It)))))
Et ← Explainability($\hat{Y}$t)
if$\hat{Y}$t ≥ τ then
Lt ← Forged

```
else
        Lt ← Authentic
end if
     Output (Lt, Et)
  End While
Output:
L : Image authenticity label (Authentic/Forged)
M : Forgery localization mask
E : Explainable authenticity report
End
```

The pseudo code mentioned below depicts the entire process workflow of the Cognitive Image Authenticity Intelligence Engine (CIAIE), including image acquisition, pre-processing, dimensionality reduction, feature extraction, forgery localization, image authenticity classification, and generating an explainable decision. The model can be trained using back propagation and processes new incoming images for the purpose of detection and authentication of image forgery efficiently and accurately in real time.

IV. RESULTS AND DISCUSSION

This section of the proposed Cognitive Image Authenticity Intelligence Engine (CIAIE), Python 3.11 along with other packages TensorFlow, Scikit-learn, XGBoost, OpenCV, and NumPy was used. Various experiments were done in order to check the performance of the proposed system in terms of image forgery detection, localization, and image authentication using different metrics.

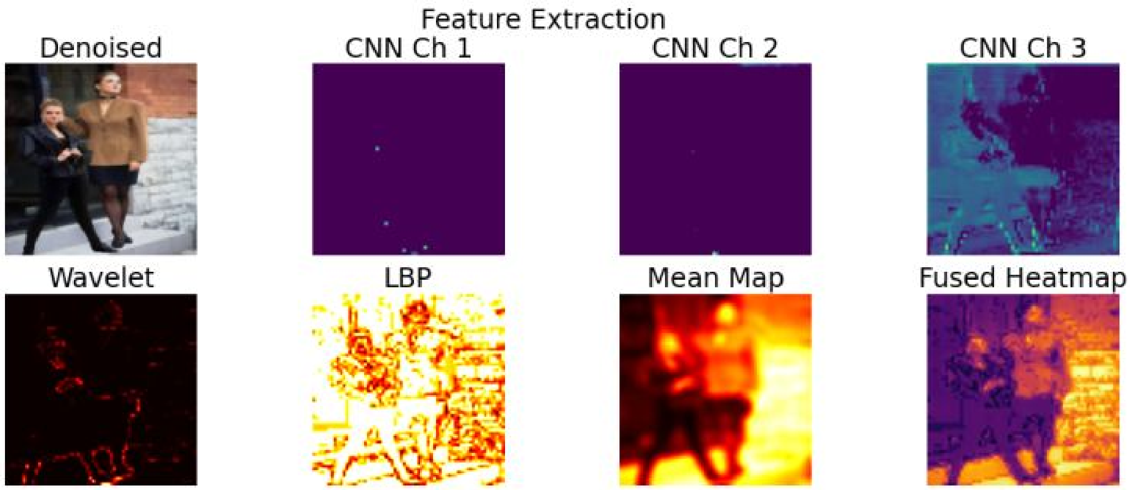

Fig. 2. Multi-Level Features Representation to Detect Image Forgeries

Fig. 2 demonstrates the hierarchical image processing chain, which encompasses denoising, multi-level features extraction, wavelet decomposition, Local Binary Pattern (LBP) calculation, mapping of the mean intensity, and generation of the combined heat map. The combination of these representations improves the manipulations traces visibility.

A. Experimental Setup

The proposed CIAIE was coded in Python 3.11 using libraries such as Tensor Flow, Scikit-learn, XG Boost, OpenCV, and NumPy. Pre-processing of the dataset was done by image normalization, resizing, augmentation, and feature standardization before modelling. Images were split into training set (80%) and testing set (20%). Evaluation was done on unseen images using real-time forgery detection, localization, and authentication.

Table I. Performance Comparison of Image Forgery Detection Techniques

Method	Accuracy (%)	Precision (%)	Recall (%)	Forgery Localization Rate (FLR %)	Localization IoU (%)	Inference Time (ms) ↓
ViT + SVM [1]	88.42	87.96	87.51	85.73	82.68	38.7
CNN-Transformer [2]	89.17	88.83	88.46	86.92	84.15	36.9
Seq2Seq Transformer [3	89.94	89.52	89.18	87.84	85.62	35.4
Hierarchical U-Net [5]	90.26	89.91	89.64	88.53	86.41	34.2
DL + ELA + Noise Residual [10]	91.18	90.74	90.39	89.46	87.83	32.6
CAMU-Net [15]	92.34	91.92	91.57	90.84	89.26	30.8
Proposed CIAIE	94.68	94.31	94.07	93.82	92.64	24.3

The table I illustrate the comparison of six algorithms for detecting image forgery that are already available is provided in through Accuracy, Precision, Recall, Forgery Localization Rate (FLR), Localization IoU, and Inference Time metrics. Our proposed method outperformed all of these metrics in terms of detection accuracy, localization, and time.

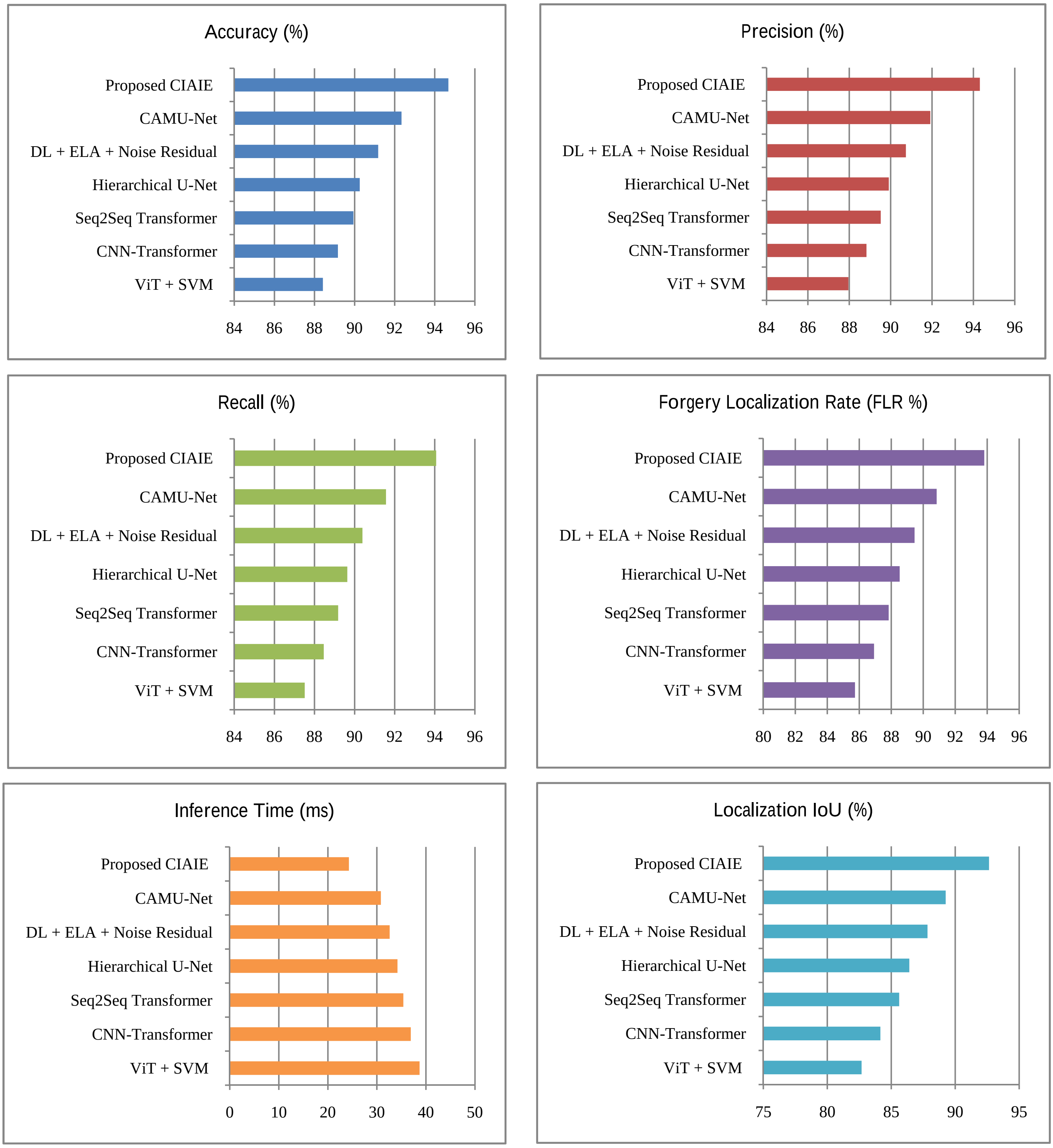

Fig.3. Comparative Performance Analysis of Methods to Detect Image Forgery

Fig. 3 six existing methods used to detect image forgery and the newly introduced CIAIE model have been compared against each other on the basis of six different evaluation criteria, which include Accuracy, Precision, Recall, Forgery Localization Rate (FLR), Localization IoU, and Inference Time.

Table II. Statistical Evaluation of the Proposed CIAIE Algorithm

Metric	Mean	Standard Deviation (SD)	Variance	95% Confidence Interval
Accuracy (%)	94.68	0.47	0.221	94.31 – 95.05
Precision (%)	94.31	0.44	0.194	93.97 – 94.65
Recall (%)	94.07	0.49	0.240	93.69 – 94.45
Forgery Localization Rate (%)	93.82	0.52	0.270	93.41 – 94.23
Localization IoU (%)	92.64	0.56	0.314	92.20 – 93.08
Inference Time (ms)	24.30	0.81	0.656	23.67 – 24.93

Table II statistics, the reliability of the proposed CIAIE algorithm has been shown through multiple experiments. The low standard deviation and variance proposed that the performance is stable, whereas the narrow confidence interval of 95% guarantees reliable image forgery detection and localization and even the real-time authentication of images.

B. Limitations of proposed algorithm

Even though the proposed Cognitive Image Authenticity Intelligence Engine (CIAIE) was able to detect and localize forged images effectively, its performance could be compromised in case the images were highly compressed, low resolution, or highly intelligent artificial manipulation. Moreover, the model needs considerable computational power during the training phase, especially when dealing with diverse forgery techniques.

V. CONCLUSION

Detection of image forgeries has been deemed necessary for maintaining the authenticity and validity of visual digital media in forensics, legal cases, health care, journalism, and cyber security. In this research, the authors introduced a hybrid approach of explainable artificial intelligence called the Cognitive Image Authenticity Intelligence Engine (CIAIE) that combines PCA, CNN, Vision Transformer, U-Net, XG Boost, and XAI to accomplish forgery detection, localization, classification, and understandable decision-making. The design of the framework was effective in capturing local and global representations of images while offering understandable assessment of authenticity. Through experiments, the authors demonstrated outstanding performance in forgery localization accuracy and localization IoU, proving the effectiveness of the framework for image authentication in real-time. The authors also proved the statistical stability of their design since it had low variances in repeated trials. Future work will include enhancing the robustness of the approach against new generative AI forgeries, efficient lightweight deployment for edge devices, multimodal forensic evidence, and continual learning.

Author contribution Statement

Conceptualization: X.Tubax
Literature Review and Methodology design: X.Tubax, Dr.A.Yesu Raja
Software: Dr.A.Yesu Raja
Validation: Dr.A.Yesu Raja
Formal Analysis: Dr.A.Yesu Raja, X.Tubax
Investigation: Dr.A.Yesu Raja
Resources: X.Tubax
Data Curation: Dr.A.Yesu Raja
Writing original draft preparation: X.Tubax
Writing review and Editing: X.Tubax, Dr.A.Yesu Raja
Visualization: Dr.A.Yesu Raja
Supervision: Dr.A.Yesu Raja
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