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Hybrid Deep Learning Convolution Neural Network Scheme for Enhanced Human Activity Recognition System in Security Surveillance

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ABSTRACT

Nigeria continues to experience a high security breach with the attendant loss of lives and properties worth in billions especially in the North-East as ravaged by insurgency, kidnapping and other forms of crime that have overwhelmed law enforcement agencies. Technology have been explored to help curb security threats and improve surveillance. This study proposes an enhanced human activity recognition system with hybrid deep learning fuzzy convolutional neural network. We utilize dynamic agile development mode using the python IDE for training and testing the machine learning models. The CNN-Fuzzy model was trained with 3,500 dataset extracted from 7 classes of the UCF Crime dataset which was further split into 70:30 ratio for training and test purposes. The model after 30 epoch with training and validation accuracy of 0.9954 and 0.9954 yielded a prediction accuracy of 97.14%, Recall of 97.14%, F1-Score of 96.83% and precision of 114.2 outperforming the existing system making it an efficient tool for security surveillance to mitigate security breaches and generate early warning signals for security agencies.

1. INTRODUCTION

Nigeria continues to witness increased insurgence and violent attacks, rapid spree in terrorism from its Northern region, has called for questions as to their funding (Atuduhor et al., 2024; Osegboun and Oladipo, 2023). There is also a rise in the facts that children are now found to be missing. Missing children cases are often classified into disappearances, and kidnap/abduction (Aghware et al., 2023b, 2023a). Studies have reported that over 6,270 teenagers have been reported missing, with over 4,620 as teenage girls (Akazue, Okofu, et al., 2024; Saminu and Mohammed, 2022). The rise in the number of missing cases – and in recent times, are attributed to feats such as parent's inability to oversee their children (Suleiman, 2022).

Kidnapping and abduction violence cum crimes can take place anywhere, anytime and in any order – from playground, supermarket, and even in our very own homes (Aleyomi and Olajubu, 2024). New sensor-based IoT system can enhance safety and help their parents by constantly emitting their children's location via short messaging. This system can help their family to monitor the children anywhere and anytime (Ejeh et al., 2024; Ifioko et al., 2024). The nature of child monitor utilizes technology to ensure considerable reliance is on the systems design and operation. IoTs have become critical feat to monitor and tracks objects' activity in/with real-time processing. Its overlay ranges from coverage sensors with controllers, wearables and home monitors. It yields such capability via its geo-fencing, state monitor and alerts to caretakers (Shoeibi et al., 2022).

1.1 ICT-Rich Monitor and Alert Scenario

ICT-rich tech have permeated all known fields with ground breaking innovation that has transformed how we live, work and play (Allenotor et al., 2015).

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Computers play a major role in the improvement of the twenty-first century society from healthcare to retail, academia, security, etc (Malasowe, Aghware, et al., 2024; Nahavandi et al., 2022). While many believe that activity recognition in confined settings can yield issue that needs to be resolved, also human action detection in complex scene still pose numerous challenges due to the dynamic shifting stances, and backgrounds of people inherent in the captured image(s) (Malasowe, Okpako, et al., 2024). The birth of artificial intelligence assistive technologies and its learning imperatives in surveillance/security has drastically improved safety. Innovative computer vision and image classification also has added value to surveillance with high level of accuracy and precision. Minor inter-class differences poses great challenge to image recognition; while, large intra-class variations are birthed by factors such as extreme occlusion (Muhamada et al., 2024), crowded backdrops and scenes, low image resolution, target motion fluctuations, and so on (Y. Li et al., 2020). In a smart city, action recognition is crucial and its accuracy can degrade resulting from interference of, or complex background. Thus, it is infrequently effective in real-world practice/use (Xiong et al., 2022). Automating the human physical activity (as anomaly) detection has become critical to pervasive computing, and in human behaviour analysis (Jacob and Monachan, 2021). Recognizing captured image activities from video sequences is a primary function of intelligent surveillance system. This growing popularity is due to their rising applications in several sectors such as surveillance, human fall detection, health, and sports analyses. For use in smart environment, any questionable behaviour is reported to the appropriate authorities (Ejeh et al., 2022). Assisted living can facilitate constant monitor of patients' action (Oladele et al., 2024). Captured image from video data-streams entails: (a) to first, learn activity representations against known templates, (b) label cum classify them against known, predefine samples, and (c) test/match them with inputted data for classification task (Safriandono, Setiadi, Dahlan, Rahmanti, et al., 2024). Activity recognition seeks to help identify from real-world image-based records, human activity that are therein classified to underpin what actions are being expressed (Muslikh et al., 2023b). It fuses properties to include action recognition, intention and narrative comprehension. Human activity recognition (HAR) is tasked with identifying and analysing behaviours and environmental interactions, notably whole-body and limb movements (Rashid et al., 2021). Movements such as walking, exercising, and other forms can be quite difficult to also predict as it requires large volumes of sensor-based, unlabelled data captured as images from video footage, that are subject to factors such as lighting, background noise, and scale variation (Akazue, Edje, et al., 2024; Han and DeSouza, 2009; Herdiansyah et al., 2024). To address these difficulties, there is the need for the implementation of an enhanced machine learning approach to improve on the predictive accuracy of the model.

1.2. IoT-Enabled Image Capturing

Ukadike et al. (2023) explored IoTs as a wearable device, integral tracking device that enhances safety security of individuals. IoTs are a versatile, low-cost solution for image capture, tracking and monitor with real-time communication capabilities (Ukadike et al., 2023). Its adaption yields navigation features to upscale their safety and confidence. Radio Frequency Identification (RFID) emerged as veritable solution to ease object track with the ability to yield accurate real-time data with robust and versatile mean to explore techs. Its demerit is with interference, and its cost-effectiveness (Malasowe, Edim, et al., 2024). RFID tags can monitor objects and Akpoyibo et al. (2022) developed a pervasive tracker for physically challenged persons to cater to their diverse user needs (Akpoyibo et al., 2022). Binitie et al. (2023) used IoT to capture images and showcase RFIDs feats in safer transportation feats (Binitie et al., 2021; Obruche et al., 2024).

Need for 24-hour visual surveillance in security-prone and high value targets have risen due to increased theft and vandalism. A majority of today's surveillance systems have cameras, and a level of manpower is needed to monitor and process the visual data that is obtained from the process (Joloudari et al., 2022). While this task cannot be delegated to human resources alone, there resides the risks of detection and scene comprehension that require on-the-spot observation over a period of extended time (Og and Ying, 2021; Okonta et al., 2013, 2014). To this end, studies have argued that attention to visual surveillance is much beneficial and a proactive approach to safety (Upadhyay and Sampalli, 2020). Learning algorithms have become the next stage in evolution and action to aid image recognition as they have steadily outperformed conventional methods with the exploration of convolution networks' success in computer vision (Jiang et al., 2019). With human action recognition (HAR) to detect human behavioural changes, it also is used to detect abnormalities in captured image scene for surveillance with mobility in the temporal domain (Mohd Ibrahim et al., 2022).

Machine learning knows strong, concise representation of an action is crucial to action recognition as the action's representation also impacts how well the learning scheme also perform (Sun et al., 2018). Studies also believe that action identification in confined spaces, and detection can be quite obscure in real-world cases (Hasan et al., 2023) and does face numerous challenges due to constant changes in human positions, views, and backgrounds (C. Li et al., 2019). The majority of current research on classifying videos is based on deep learning. It delivers accurate and timely data of people's activities by utilizing sensory data accessible in today's sensor-rich environ. Har systems identify human activity by finding and localizing such activity in the scene over time to improve comprehension of the event that is happening (Zolfaghari et al., 2018).

Eboka et al. (2025) used a sensor-based image capture vision for recognizing human activity records and monitors human activity using visual sensing of the environ vis closed circuit TVs strategically installed/deployed under surveillance be it on highways, schools, banks, industrial and residential areas (Eboka et al., 2025). Vision systems outperform other strategies in gaining societal confidence since they can identify activities via captured pixel or recorded video sequences (Omede et al., 2024). Thus, it extracts data in the environ without user-interference or wearable units. This makes it readily acceptable for/to both scientific and non-scientific spaces due to its non-intrusive feat (Obasuyi et al., 2024). If the image quality that is captured is good, this method will function effectively. Image quality can be affected by illumination changes, lighting circumstances, camera quality, and image resolution (Setiadi, Muslikh, et al., 2024). Though less expensive to design, it is crucial to recall that ambient elements such as angle of camera, lighting, and individual overlap has greater impact on vision-based human activity interaction systems (Brizimor et al., 2024; Otorokpo et al., 2024).

Deep learning (DL) a family of machine learning models based on neural networks with representation learning (Setiadi, Nugroho, et al., 2024). Their popularity in recognizing human activity can be attributed to their use of representation learning techniques, which can automatically find hidden patterns in data and generate optimal features from raw input generated from sensors without human intervention (Ibor et al., 2023). Activity recognition systems often utilize classification algorithms to classify actions as class labels. Sensor-based HAR, like other time series data, begins with segmenting data into time frames, which are then used to extract time and frequency domain features (Olaniyi et al., 2023). Traditional machine learning algorithms yields manual feature extraction – unlike its automatic mode as achieved via deep learning, which is useful in extracting complicated knowledge from large amounts of unsupervised data (Geteloma et al., 2024).

Okpor et al. (2024) effectively used DL to resolve inherent difficulties in image and voice recognition stating clearly that DL are divided into three (3) form namely generative, discriminative, and hybrid (Okpor, Aghware, Akazue, Eboka, et al., 2024). Generative model learns a train-data real distribution and makes changes to yield new samples with the same probabilistic distribution as in restricted Boltzman machine, deep autoencoders, and sparse coding (Kakhi et al., 2022). The discriminative mode seeks to approximate posterior distribution classes to directly predict the probability of the output given an input, p(y|x). The most widely used include convolutional neural networks (CNN) and recurrent neural networks (RNN) (Okofu et al., 2024). Studies have explored both modes to extract more useful predictor features. Lastly, the hybrid models seeks to fuse or combine both the generative and discriminative approaches. With respect to human activity recognition system, studies have proven that the combined CNN with other generative or discriminative models have produced more accurate predictions in the domain it is deployed (Binitie et al., 2024).

CNN (ConvNet) is a well-known design for deep learning techniques. It consists of several layers utilized for image processing and object detection. Proposed by Yann LeCun as LeNet in 1988 – its algorithm is widely used for image processing to identify satellite images, processing medical imaging, forecast time series, and detect anomalies. It learns internal representations of raw sensor data without requiring feature engineering expertise (Manickam et al., 2022). Thus, its popularity for use in analysis and activity recognition. CNN performs convolution on sensor data using several hidden layers. CNN consists of four layers: convolutional, pooling, dense (completely linked), and softmax (Kizilkaya et al., 2022).

Joshi et al. (2020) investigated image tracking with activity scheduling system that sought to address face-to-face monitor using CNN. The system integrates wearable device image trackers via cloud-based application to yield real-time location tracker and activity scheduling functions. The system offered the potentials to enhance parental oversight (Joshi et al., 2020). Lu (2022) used CNN for face detection to handle toddlers' curiosity to explore potentially dangerous situations. It monitored movements and alerted parents of any hazardous objects. Its challenges were in optimizing algorithm accuracy and minimize false alarm (Lu and Rakovski, 2022).

Krishna et al. (2023) deployed CNN in smart child tracking with the goal to help parent utilize the face detection monitor of their children's movements. System sought to yield real-time location, and enabled parents to receive tracking data via SMS (Krishna et al., 2023). Its demerit in optimizing sensor performance as well as yield reliable transfer of data, was resolve via refined design to address potential limitations to improve user experience and adoption. Okpor et al. (2024) advanced works of Lu (2022) using CNN with long-short term memory learning in vision-based system to monitor human activity safety indoors. They explore multi-factor authentication in the system to monitor imminent emergencies, potential dangers (Okpor, Aghware, Akazue, Ojugo, et al., 2024).

1.3 Study Motivation and Goal(s)

With the reviewed literatures, available image detection system lacks comprehensive fusion of CNN in existing technologies; And thus, results in limited functionality, which in turn yields degraded performance. The study is motivated thus (Hennink and Kaiser, 2022):

1. Limited functionality in IoTs without the advanced features like real-time monitor will generate reliability issues (Aghware, Okpor, et al., 2024).
2. Reliability: Compromised systems due to insufficient use of wearable IoTs with its inaccurate data recorded cum failure to transfer data undermine the effectiveness of the system (Ojugo et al., 2023).
3. Sensor Network Performance: Problem to optimize network of sensors to ensure reliable communication. Utilization of sensors that fuses data acquired via multi-unit to enhance its tracking accuracy (Brizimor et al., 2024; Estes and Streicher, 2022; Obasuyi et al., 2024).
4. Optimized Accuracy with Reduced False Alarms: Yoro et al. (2022) identified the need to optimize accuracy and minimize false alarm in toddler tracking. To address these requires continuous refinement of deep learning algorithms, including data augmentation techniques and model fine-tuning, to improve recognition accuracy and reduce false alarms (Yoro, Aghware, Akazue, et al., 2023).

To overcome these, we implement the smart child-tracking system as thus: (a) develop comprehensive understanding of existing child monitoring and tracking techs with regards to their capabilities, limitations, and ethics, (b) adopt latest trends in IoTs relevant to child track/monitor, (c) identify design requirements to implement our smart child tracking in lieu of accuracy, reliability, and user-friendliness, (d) implement a prototype tracking system with integrating embedded systems such as controllers, sensors, and communication modules, and (e) evaluate its effectiveness and usability via real-world test scenarios and user feedback (Wemembu et al., 2014). It promises revolutionary change in the monitor kids with improved user-trust, greater functionalities, assured user acceptance and better reliability.

2. Materials and Methods

2.1. The Experimental Framework

The proposed method is as in Figure 1 with its steps explained as thus:

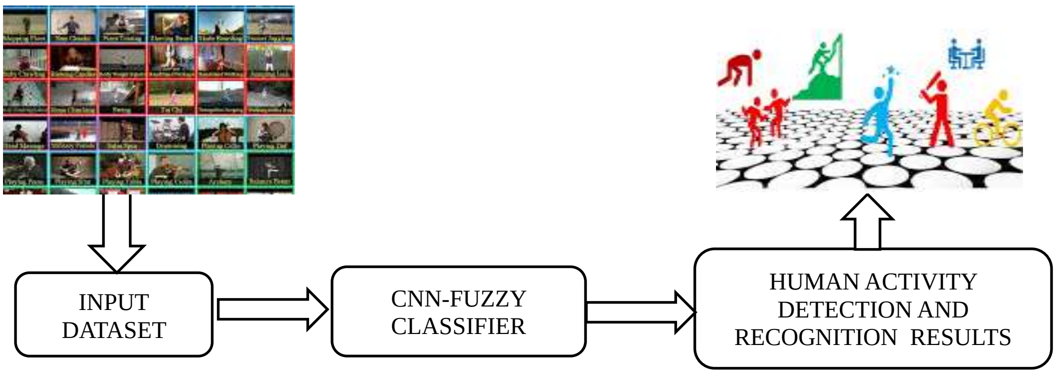


Figure 1. The Proposed Fuzzy CNN-based Image Recognition Methodology

1. **Input Data** is retrived via unstructured form (Bayer et al., 2023) captued image for which, each image is extracted from surveillance videos of the human action. Dataset is available online at [web]: kaggle.com/datasets/odins0n/ucf-crime-dataset (UCF-crime dataset) with 1900 videos grouped into: accident, burglary, abuse, arson, assault, fighting, robbery, shooting, stealing, shoplift, vandalism, etc. Dataset consists of a total 1,377,653 images with 964,357-image recordset for training, and test as 413,296-images.

2. **Preprocessing:** (a) first encodes the data from its natural state(s) to an appropriate equivalence using the one-hot encoding technique. It then explores

the DWT to use its bi-orthogonal filters, based on wavelet decomposition mode to denoise the image dataset. The filter splits all the image data into smaller, easy manegeable segments, removes duplicate and missing values (Ako and Abugor, 2018), ensures the resultant decomposed image yields right output form, converts all data into their numeric equivalent, and encodes data onto the appropriate form to be used by the ML (CNN-Fuzzy model).

3. **Fuzzy Set** – aids ML reasoning systems to emulate human capacity to reason via its degrees of certainty (Ako et al., 2021; Ochuko et al., 2009) that aids decision support recommendation in managing all (non)-binary user preferences. A fuzzy system creates set of if-then-else ruleset that chooses between different control actions and transforms such into a fuzzy value (Ako et al., 2020) . A fuzzy classifier model assigns a class label to an object based on an object' s description, so that it can also predict each class label. Object descriptions are vector values with feats relevant for such classification task. Classifier learns to predict a class labels via training algorithm and its accompanying dataset. If a training data set is not available, classifier is designed to learn apriori (prior knowledge) so that trained, it classifies objects. Thus, the rule-based classifier focuses on if-then rules with actions and possible outcomes, constructed as a user specifies its class rules and linguistic variables (fuzzy set) that helps tune a fuzzy set in line with such class rules. For example: If Math Error is medium and is small, Then Class 1 If Math Error is medium and is large, Then Class 2 etc (Ojugo and Yoro, 2021b).

Fuzzy cluster scheme groups data as linguistic feature homogeneous classes known as clusters so that items in the same class are as similar as possible and vice-versa. Clustering seeks to compress data with a large number of samples are converted into small number of representative clusters . Depending on data and task, different types of similarity measures are used to identify classes, to control how clusters are formed. Examples of values that can be used as similarity measures include distance, connectivity, and intensity.

4. **CNN Model Phase** – as in Figure 2. Its input is tasked with image dimensioning onto a compatible size, whose output is fed into the convolutional layer to extract its best feature(s). The extracted image is scanned and pooled at its convolutional layer to the fully connected layer via rendering (Ojugo and Yoro, 2021b). These are further explained as thus:

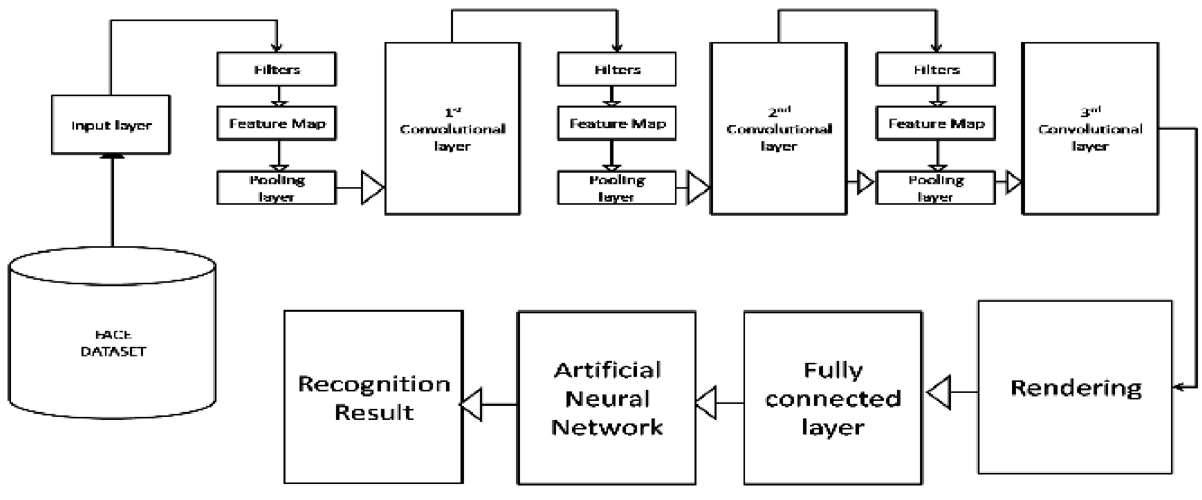


Figure 2. The Convolution Neural Network

- **Step-1 – The Input Layer** retrieves its input data via the wavelet transform, and dimensions it via the format (h x W x C) with h as image height, W as weight, and C is color channel. The dimension (1960 x 512 x 3) yields the value attributes cum image (data) size as fed to convolutional layer, which is accomplished via feature map, filtering mode and pooling process respectively.
- **Step 2 – Filtering** scans image to extract key feats that specify image dimensions as in Equation 1 – which in turn, yields the matrix that ensures compatibility of features map as its output as in Equation 2 to yield the convolutional padding and kernels size (Dosovitskiy et al., 2020; Emebo et al., 2019). It uses the ReLU (Rectified Linear Unit) to introduce the required nonlinearity into the image so as to help it transform all negative-to-null values.

$$F_o = (F_w * F_h * d) \quad (2)$$

$$F_o = \left[\frac{F_i + 2_p - k}{s}\right] + 1 \quad (3)$$

- **Step 3 – Pooling:** With features mapped against scanned pixels, the system pools via maximum mode to select only pixels with the highest value to form input for the convolution layer.

- **Step 4 – Convolution Layer:** Pooled image yields input to convolution layer, which selects only images with highest values. Our 5-by-3 matrix filters image dimension to form convolutional layer as in Equation 4. Also, it then generates pools of 2nd-and-3rd pool-generation as in Equation 5.

$$C_O = ((w * h) + 1) * \text{nf} \quad (4)$$

$$C_O = \big((w * h * np) + 1\big) * nf) \quad (5)$$

- **Rendering** sums up all the feature maps extracted to yield an activation size with a matrix array of the best features of all the pooled image. CNN introduces light intensity to enhance quality of the image (Yao et al., 2022) via Equation 6. Also, Equation 7 is applied to the last layer to ensure emitted radiance in image pixel (Eed et al., 2024; Pillai, 2022).

$$A_s = (w * h * d) \quad (6)$$

$$L_s(x, y) = L_e(x, y) + \int f_r(x, w, y) L_f(x, w) \cos\theta dw \quad (7)$$

- **Fully Connected Layer** flattens otput images for training phase to learn the image features for recognition as in Equation 8. It is monitored for accuracy to ensure enhanced generalization using – with L is loss function, k is number of observations, P is prediction, and D is training target.

$$L = \sum_{i=l}^{K} (P_i - D_i)^2 \quad (8)$$

- **Output Layer** yields the desired output via a Softmax activation that transforms all its vector features into the designated probability distribution of the image input using the Equation 9 (Zhang et al., 2019).

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad (9)$$

3. Result Findings and Discussion

3.1. Model Performance and Benchmark

The model was trained and after 30 epochs yielded a training and validation accuracy of 0.9954 and 0.0029 with a loss and validation loss of 0.0109 and 0.1733 respectively (Ojugo et al., 2013). The accuracy and loss graph in Figure 4.6 shows the trajectory of the graph. The confusion matrix in Figure 4.7 shows the actual and predicted result of the model (Muslikh et al., 2023a; Safriandono, Setiadi, Dahlan, Zakiyah, et al., 2024). From the confusion matrix the model accurately predicted the different categories of crime contained in the dataset as agreed by (Allen et al., 2024; Sinha, 2024) as in Table 1.

Table 1. Classes of Activity

S/N	Dataset Class	Accurate Predictions
1	Abuse	15
2	Arrest	19
3	Assault	0
4	Burglary	24
5	Normal	28
6	Robbery	1
7	Vandalism	15

The confusion matrix shows 3-groups of evaluation; two for the crime and one normal respectively. The cumulative score of the model's prediction based on the evaluation metrics is in Table 2.

Table 2. Classes of Accurate Prediction

Metrics	Scores	(%)
Accuracy	0.9714	97.14
Precision	1.1420	114.2
Recall	0.9714	97.14
F1-Score	0.9683	96.83

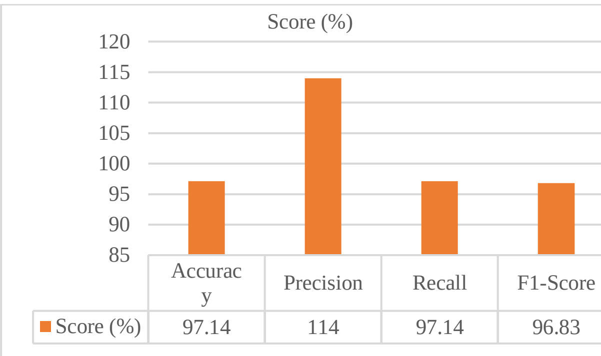


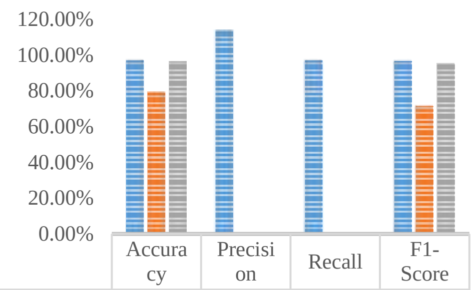
Figure 4. Model Performance evaluation

Security of live and properties of the citizens is said to be one of the cardinal priorities of government and governance, over the years this critical component of social integration, coexistence and development have experienced a downward turn with the plethora of security challenges that appears to have overwhelmed the law enforcement agencies and government. From theft to robbery, burglary to arson, kidnap to first degree murder, the list of crime and criminality perpetrated across the country on daily basis has reached an alarming scale with the people helpless and government and their agencies put in a state of utter confusion. To mitigate the ever-evolving security challenge, several approach and method have been deployed for the improvement of security surveillance for the generation of early warning signal to increase mitigation efforts but with little or no positive impact as most of these have been manually driven.

With the emergence of computer technologies and artificial intelligence and her subset of machine learning innovation in security and surveillance has also drastically improved with enhancement in security and safety of the society deemed more critical above all. The innovations in computer vision and image classification also has added value to surveillance with high level of accuracy and precision. This research therefore proposed an improved machine learning model for human activity recognition using convolutional neural network and fuzzy logic algorithm for the detection of security threats in surveillance video dataset. The model which is a hybrid model that integrated a fuzzy logic model to a three-layer deep convolutional neural network (CNN) model was trained and tested with 3,500 image datasets having 7 classes (Abuse, Arrest, Assault, Burglary, Normal events, Robbery and Vandalism) with a 70:30 ratio for the training and test dataset was extracted from the Kaggle UCF crime dataset and the model yielded a training and validation accuracy of 0.9954 and 0.9954. Furthermore, the model yielded a prediction accuracy of 97.14%, Recall of 97.14%, F1-Score of 96.83% and precision of 114.2 outperforming the existing system when evaluated against the listed evaluation parameters and it is suitable to be deployed for early warning signal generation for incidences of criminality in the society.

3.2. Comparison

Figure 5 yields performance comparison between existing and proposed model, which agrees with (Oladele et al., 2024; Omoruwou et al., 2024).



	Accuracy	Precision	Recall	F1-Score
New System	97.14%	114.20%	97.14%	96.83%
Altaval et al (2021)	79.55%			71.63%
Pavliuk and Mishchuk (2022)	96.48%			95.44%

Emordi et al (2024) model was a pre-trained VGG16 CNN model integrated with a support vector machine (SVM) for human activity recognition system and it yielded an accuracy of 79.55% with an F1-Score of 71.63% respectively (Emordi et al., 2024). Odiakaose et al. (2024) which is a deep learning using continuous wavelength for human activity recognition also yielded an accuracy of 96.48% with an F1-Score of 95.44% respectively. From the foregoing, the new system outperformed the existing models (Odiakaose et al., 2024).

The new system was evaluated using standard evaluation metrics such as model accuracy, precision, recall/ sensitivity and F1-score respectively. Also the new system recorded a training and validation accuracy of 0.9954 and 0.0029 with a training loss and validation loss of 0.0109 and 0.1733 after 30 epochs (Ojugo et al., 2023).

4. CONCLUSION

This work was underpinned by the work of Rajput et al. (2022) which developed a CNN model for the surveillance and with the presence of blur, irregular and unstable dataset of both video and images unfortunately their work did not report the efficiency of the system with respect to standard evaluation metrics of accuracy, recall, precision and F1-score respectively. Our model was developed using UCF crime dataset and was tested and compared with two other related works by Altaval et al (2021) which developed a a pre-trained VGG16 CNN model integrated with a support vector machine (SVM) for human activity recognition system which yielded an accuracy of 79.55% with an F1-Score of 71.63% and Pavliuk and Misshchuk (2022) which is a deep learning using continuous wavelength for human activity recognition that produced an accuracy of 96.48% with an F1-Score of 95.44%. Furthermore, our model outperformed these models with a higher performance accuracy making it more efficient for early detection of security and surveillance threats within an environment taking data from CCV video stream.

Conflict of Interest

The authors declare that there is no conflict of interest.

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