International Journal of Multidisciplinary Research and Growth Evaluation.

A Hybrid Algorithm for Improving Recognition System in Human Activities

Kizito Eluemunor Anazia [1*], Ogheneochuko Ubrurhe [2], Irikefe Friday Eti [3], Vivian Onyinye Okeke [4], Idongesit Ofonime Francis [5]

[1, 2, 3, 5] Department of Information Systems and Technology, Southern Delta University, Ozoro, Nigeria

[4] Department of Computer Science, Federal College of Fisheries & Marine Technology, Lagos, Nigeria

* Corresponding Author: **Kizito Eluemunor Anazia**

Article Info

ISSN (online): 2582-7138
Volume: 06
Issue: 03
May - Jun 2025
Received: 06-04-2025
Accepted: 10-05-2025
Page No: 584-591

Abstract

Recognition models often experience a drop in performance when applied to new users or when users' physical or behavioral states change, which typically requires retraining with more labeled data. Additionally, challenges arise in search domains due to object interactions and the difficulty in distinguishing similar actions performed by different individuals. To overcome these limitations, a hybrid algorithm for improving recognition system in human activities was developed. This solution combines the capabilities of Convolutional Neural Networks (CNN) and Fuzzy Logic to leverage both deep learning and rule-based reasoning. The algorithm was built using a dynamic software development methodology, an agile framework well-suited for deep learning projects. The datasets were trained and tested using Google Colab using Python, TensorFlow, and Keras libraries. This hybrid model improved the accuracy and efficiency of human activity classification and was able to manage vague or uncertain data within the data warehouse. It also accurately identified specific actions within sequences of video frames. The model achieved an F1-score of 96.83%, a recall of 97.14%, and precision of 114.2% and an accuracy of 97.14%, marking a significant improvement over previously existing algorithms.

DOI: https://doi.org/10.54660/.IJMRGE.2025.6.3.584-591

Keywords: Convolutional Neural Network (CNN) and Fuzzy Logic, Human Activity Recognition and Sensor Fusion

1. Introduction

The advent and integration of computers and related technologies have revolutionized virtually every aspect of human endeavor, introducing groundbreaking innovations that have transformed how people live, work, and interact globally [1]. Computers devices have played a critical role in shaping modern society across diverse sectors, including healthcare, retail, marketing, industry, academia, entertainment, sports, security, and research and development. Although many researchers consider recognition of activities in controlled, simplified environments a solved problem, accurately detecting actions in complex, real-world settings remains a significant challenge due to variations in human posture, viewpoints, and background conditions [2].

With the upsurge of artificial intelligence, particularly its subset, machine learning; security and surveillance technologies have witnessed notable advancements, leading to heightened societal safety and protection. Developments in computer vision and image classification have further enhanced surveillance capabilities, offering improved precision and accuracy [3]. However, recognizing events in surveillance video remains difficult due to minimal differences between activity classes and considerable variations within certain range. These variations arise from factors such as heavy occlusion, cluttered environments, low-resolution imagery, and irregular target motion [4]. In smart city contexts, action recognition plays a vital role. Yet, its utilization practically is often limited because of the interference caused by complex industrial environments, which hampers recognition accuracy [5]. Automating the detection of human physical activity has become essential in pervasive computing, human behavior analysis, and interpersonal communication systems [6].

A key capability of intelligent surveillance systems is the recognition of activities from video content, enabling them to support various applications such as fall detection, health monitoring, human-computer interaction, sports analysis, and general surveillance [7]. In smart environments, suspicious behavior can be flagged and reported to the appropriate authorities. Human activity recognition obtained from video involves learning meaningful activity representations or features, usually used for classification. In essence, activity recognition that identifies and analyzes human behavior from real-world video data is of great importance [8]. This field encompasses several subdomains, including action detection, intention inference, and situational understanding. Fundamentally, activity recognition in humans focuses on detecting and interpreting human movements and interactions with the environment, often involving full-body or limb motion analysis. In the context of security surveillance, interpreting these actions is critical for anticipating their outcomes and understanding the actor's intent, goals, or psychological state [9].

The primary objective of deploying human activity recognition systems across domains such as security, healthcare, banking, education, retail, and research, is to predict individual or group behavior based on data captured by various sensing technologies [10]. This process typically involves identifying and labeling activities through sensory data analysis, including common actions like walking or exercising. However, accurate motion prediction remains challenging as a result of the demand for extensive unlabeled sensor data and video footage that is often affected by features like lighting conditions, background noise, and scale variation [11, 12]. Implementing sophisticated machine learning methods is essential for overcoming these challenges and boosting prediction accuracy

2. Review of related literature

Activity recognition systems represent a broad and dynamic field of research, currently focused on the integration of unconventional machine learning techniques, advancements in hardware architecture, and reducing monitoring costs while enhancing safety [13]. In earlier security, surveillance, and patient monitoring systems, human operators were tasked with observing and analyzing activities. However, this approach is almost becoming impractical and costly, particularly with the demand for 24/7 monitoring and the growing number of camera feeds and sensor-based monitoring devices [14].

In [15], a hybrid algorithm incorporating Decision Tree, Random Forest and K-Nearest Neighbors (KNN) was proposed for classifying 18 different activities using the WISDM dataset. By leveraging accelerometer data collected from smartphones and smart watches, the study achieved improved classification accuracy [16]. Similarly, [17] introduced two models: one utilizing velocity sensor data and another using spatial data collected from a variety of physical exercises rather than structural data alone.

Further work by [18] introduced a quell network capable of learning discriminative spatiotemporal features while overcoming the possible drawbacks of models that rely only on key frames or key point connections. In the study conducted by [19], a deep recurrent neural network model was proposed for human activity recognition, aiming to capture extended temporal dependencies in embedded data beyond the boundaries of kernel-based approaches. Another architecture transformed time-series data from digital sensors into visual representations, achieving notable recognition performance [20].

According to [21], a catalog of human activities was compiled using data from ten publicly available sensor-based datasets. Despite their utility, such architectures face challenges in efficiently extracting features from time-series data and often entail high computational costs, rendering them less practical for widespread application. In contrast, [22] proposed a non-invasive HAR method using UAV-captured video sequences to track human movement.

In [23], a novel method was proposed for training deep video representations tailored to action recognition in compressed video streams. Similarly, [24] presented a model designed for egocentric recognition of routine activities including walking, exercising, and office tasks by integrating egocentric video and accelerometer data to enable multi-modal sensory fusion.

In [25], spatiotemporal motion features were explored using genetic programming (GP) to automatically generate motion-related scripts from a set of basic 3D operations, avoiding hand-crafted feature design. Study [26] used three wearable inertial accelerometers placed on different parts of the body to collect raw data and extracted features for classifier training. Enhanced fuzzy rules were applied in [27] to represent transitions between activity states, providing a graded assessment of movement from one state to another.

According to [28], a novel approach was introduced for monitoring human behavior through an indoor localization system based on stigmergy, with a particular focus on elderly care. This system was further refined using real-world datasets to enhance its reliability, as demonstrated in [29]. In a separate study, [30] utilized deep learning techniques to classify human activities using smartphone accelerometer data, enabling effective monitoring and timely response to potentially suspicious behaviour.

The study in [31] leveraged height and Doppler radar cross-section data obtained from multiple-input multiple-output radar systems to enhance human activity detection. Similarly [32], introduced a multi-class human activity recognition framework based on an ensemble of autoencoders, which were trained on class-specific data to reconstruct sensor signals and accurately assign activity labels. Moreover, the accuracy of data collected from wearable sensors is highly dependent on their placement on the body. Research indicates that the waist, lower back, and sternum are the most effective positions, as their proximity to the body's center of gravity improves motion capture fidelity [33, 34]. However, while visual sensors offer valuable information, they pose privacy concerns and ethical issues, making them unsuitable for certain environments or continuous monitoring [35]. In recent years, digital sensors have become widely incorporated into mobile phones and wearable activity trackers [36]. This proliferation has enabled the creation of a diverse range of applications, such as human activity recognition for tracking daily activities, monitoring military operations, assessing physical fitness, and performing gait analysis, which examines an individual's walking and standing patterns for medical and wellness purposes [37]

Building effective movement classification systems in these fields presents several challenges and requires adherence to standard procedures. Some of the primary obstacles in using inertial sensors for motion tracking include selecting appropriate features for processing, designing low-cost,

portable data collection systems, developing effective feature extraction and inference techniques, collecting data in real-world environments, ensuring adaptability to new users without frequent system updates, and deploying these systems on mobile devices while addressing processing and energy consumption concerns. Fortunately, advancements in battery technology and computational power have significantly eased the resolution of these issues [38].

3. Methodology

This system, a hybrid algorithm for improving recognition system in human activities is a deep learning-based approach that analyzes and predicts the performance of recognition in the activities of human beings. In other to achieve its objectives, the development of the systems encompasses data collection phase, preprocessing phase, feature extraction phase and reduction phase. Also the generated data are further subjected augmentation and classification for accurate recognition of activities. Convolutional neural networks techniques will be utilized to detect suspicious objects, while logistic regression will identify suspicious activities. The system will process video footage at the initial stage to detect movement within the monitored area. Upon identifying movement, the system will assess whether the individual is engaged in any behavior that could be taken a security threat. A Fuzzy model is incorporated to enhance the clarity and analysis of the dataset. The application will continuously monitor human actions and issue an alert if any suspicious activity is detected.

3.1 Analysis of the system

The system integrates a fuzzy inference system with the existing LR-CNN model to improve the accuracy classification of the prototype. Additionally, the model will be trained using a global surveillance dataset to improve its ability to recognize activities beyond those present in the locally generated dataset. This will enable the system to identify behaviors and activities that may pose security threats or concerns in the environment. The LR-CNN model will handle the classification and the fuzzy inference system will be used to identify unclear or blurred data within the region of interest make provision more précised evaluation of security and surveillance concerns at any given moment.

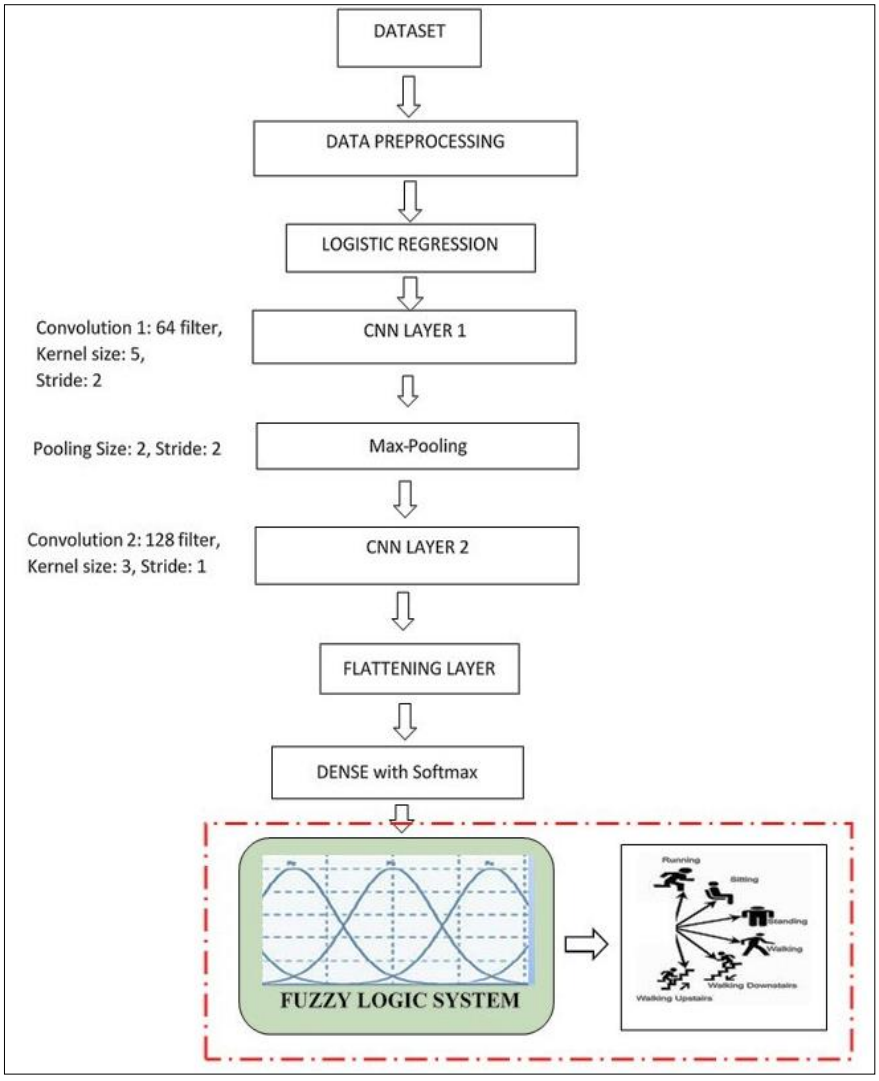

Fig 1: Architecture of the System

The system integrates the capabilities of the LR-CNN and fuzzy inference system to enhance the classification of the model. As shown in the architecture of the system in figure 1, the LR-CNN component receives the preprocessed dataset, training of the model, classification and passes the results to the Fuzzy system. The fuzzy system handles the uncertainty

found in real-world data by mimicking human reasoning and decision-making processes. It worthy of note that this method is one the appropriate methods for handling unclassified, vague or ambiguous collection of data such as unclear human activities in complex environments, which may be captured by surveillance systems like wearable IoT devices, including cameras and smartphones.

Generally, the design and implementation of hybrid algorithm for improving recognition system in human activities is basically designed in the elimination of the outlined drawbacks of using each model independently. The following are the advantages of the new system:

- It has more accurate prediction because of the detailed construction and deployment of the system using fuzzy TSK (TagagiSugeno Kang) inference mechanism.
- Early and quick recognition/ detection of threat factors within the environment to forestall security breaches
- It has the ability of detecting and classifying both local and global threat activities.
- Overcoming of noise and imprecision in the prediction due to blurriness of dataset.

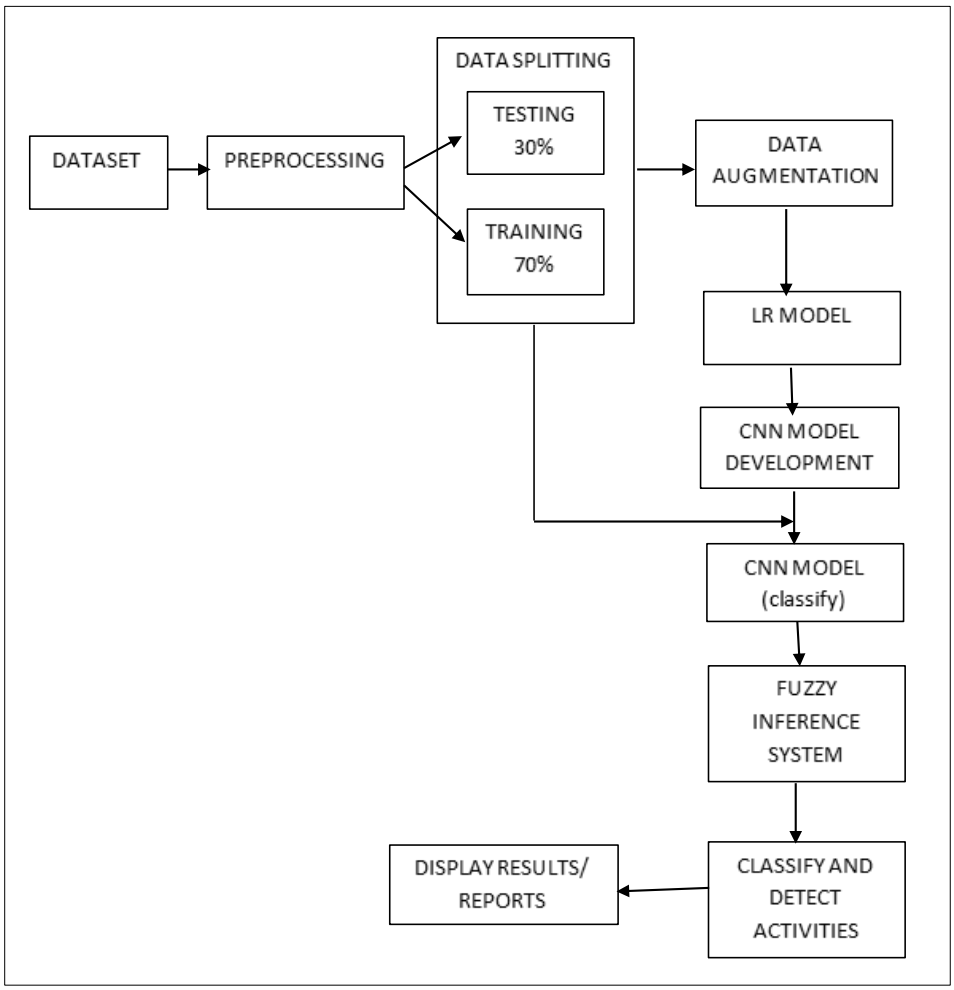

Fig 2: The flow diagram of the system

3.2. Method of data collection

The dataset used in the design of this system are globally recognized dataset used for the practical implementation of machine learning projects sourced from the Kaggle Machine Learning repository. The dataset contains 18,000 samples, with 12,600 allocated for training and 5,400 for testing. It is further organized into two folders: the human action recognition folder, which contains both training and testing subfolders. The HAR model is trained by the datasets allocated for training, while those kept to test data are reserved for model evaluation. The datasets can be accessed from the link below;

https://www.kaggle.com/datasets/odins0n/ucf-crime-dataset

3.3. Datasets

These hybrid algorithm models play a crucial role in surveillance operations, enabling the exploration of human actions and intentions. These models help predict the next move of a subject and can mitigate potential risks, such as criminal activity or violence. As datasets obtained from Kaggle Machine Learning repository, they are basically the UCF-Crime dataset. This large-scale dataset consists of several hours of video, comprising 1,900 long, real-world monitoring clips. It includes one normal activity and several security threats, like burglary, vandalism, explosions, shoplifting etc. The dataset contains 1,377,653 images, with 1,266,345 designated for training the datasets while for testing exercises, 111,308 datasets where used, totaling 11.57 GB in size. Seven classes dataset were extracted, totaling 3,500 images sourced from the surveillance videos. Of these, 2,450 images (approximately 70%) were used for training, while the remaining 1,050 images (30%) were used for testing.

3.4. Preprocessing

The preprocessing stage involves several steps to organize the dataset for use, address any missing or incorrect data, and augment the dataset to enhance both its quality and quantity during the model's training and testing.

a. **Data Collection:** Camera-provided images may suffer from reduced quality, so it is crucial to train the model to adapt to these conditions effectively.
b. **Formatting:** After cleaning the dataset, it must be formatted appropriately for further processing.

Data preprocessing is a critical practice in data mining that transforms raw, unstructured data into a structured and optimized format. Key tasks in data preprocessing include:

- Data Cleaning: This involves identifying and fixing errors, inconsistencies, and missing values within the dataset to enhance the data quality.
- Techniques used: Regression is used to track and fix values that are missing.
- Data Integration: Merging data from various sources into a single, cohesive dataset for analysis
- Techniques used: Schema integration.
- Data Reduction: Reducing the volume of data and still retains vital information to enhance efficiency.
- Techniques used: Data compression.
- Data Transformation: Modifying the structure so that it will be suitable and easy to analysis.

4. Results and Discussion

The model was trained and tested using the UCF Crime dataset, which is designed for real-world crime detection through surveillance videos. This dataset includes images extracted from each video, covering fourteen distinct categories of criminal activities: like burglary, vandalism, explosions, shoplifting etc. The data is organized into separate folders that are used for training and testing purposes and every 10th frame from each full-length video is extracted, compiled dataset for each activity category.

The dataset, sourced from the Kaggle repository, totals 11.57GB of video streams, which were converted into image datasets for the model's training and testing purposes. Because of the enormous size of the dataset, we narrowed the focus to seven categories that will be used to train and test datasets of the model. Additionally, the total dataset from these selected classes was reduced to 3,500 images, with a 70:30 ratio split between training and testing. It's important to highlight that the datasets are divided into seven classes, allows the model to carry out multiclass classification, accurately assigning images to the appropriate security threat category or identifying them as normal activities.

4.1. Loading Datasets

To load the dataset into the deep neuro-fuzzy model, first downloaded the datasets and narrowed down from 14 categories to 7 classes, which were then placed in separate folders for the purpose of training and testing. As a result of the original datasets, it was compressed into a zip file and uploaded to the Google Colab file menu. Afterward, the file was unzipped and loaded into the model. This step was necessary because the full dataset, which contained over a million data points, was too large for direct uploading. The size of the datasets was reduced to 3,500 images, which makes it more manageable for training and testing purposes.

4.2. Model Outputs

The deep neuro-fuzzy model consists of the following layers; input layer, three hidden layers, and output layer. The hybrid algorithm for improving recognition system in human activities is built to predict and classify potential security threats by analyzing human activities in surveillance video frames. The images obtained from the datasets were used for the model's training, testing, and validation phases. The datasets used was extracted from Kaggle's UCF Crime dataset, which focuses on real-world crime detection from surveillance footage. The original dataset includes images from videos associated with 13 different criminal activities paired with a single normal event. However, the datasets was filtered to include six criminal activities and one normal class, resulting in seven classes in total. The multiclass classification performance of the hybrid algorithm for improving recognition system in human activities is attained by these various adjustments.

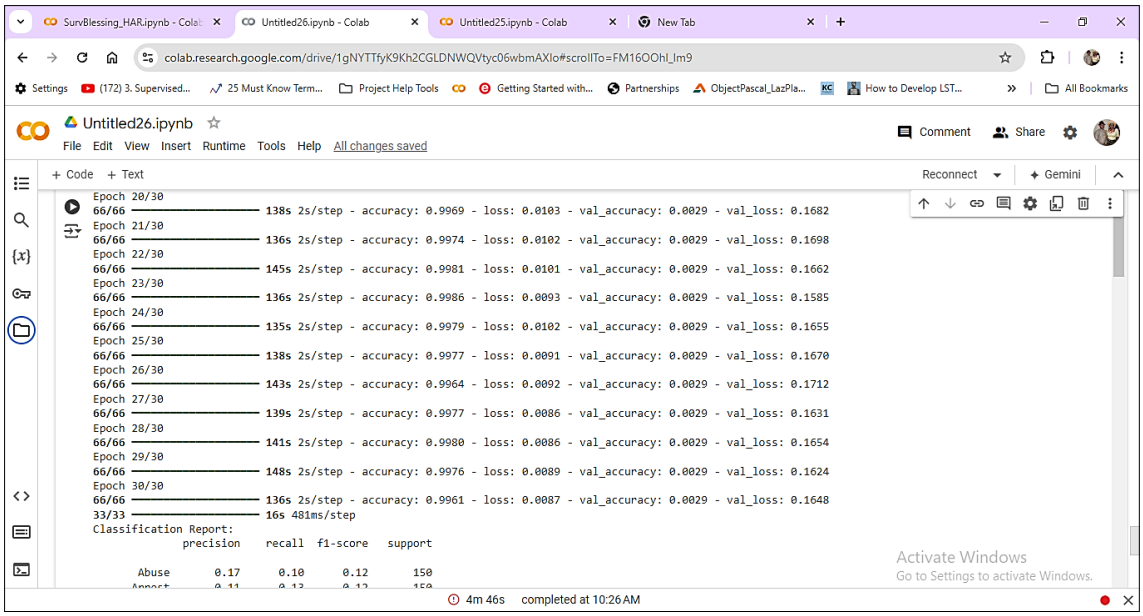

Fig 3: The system's output model

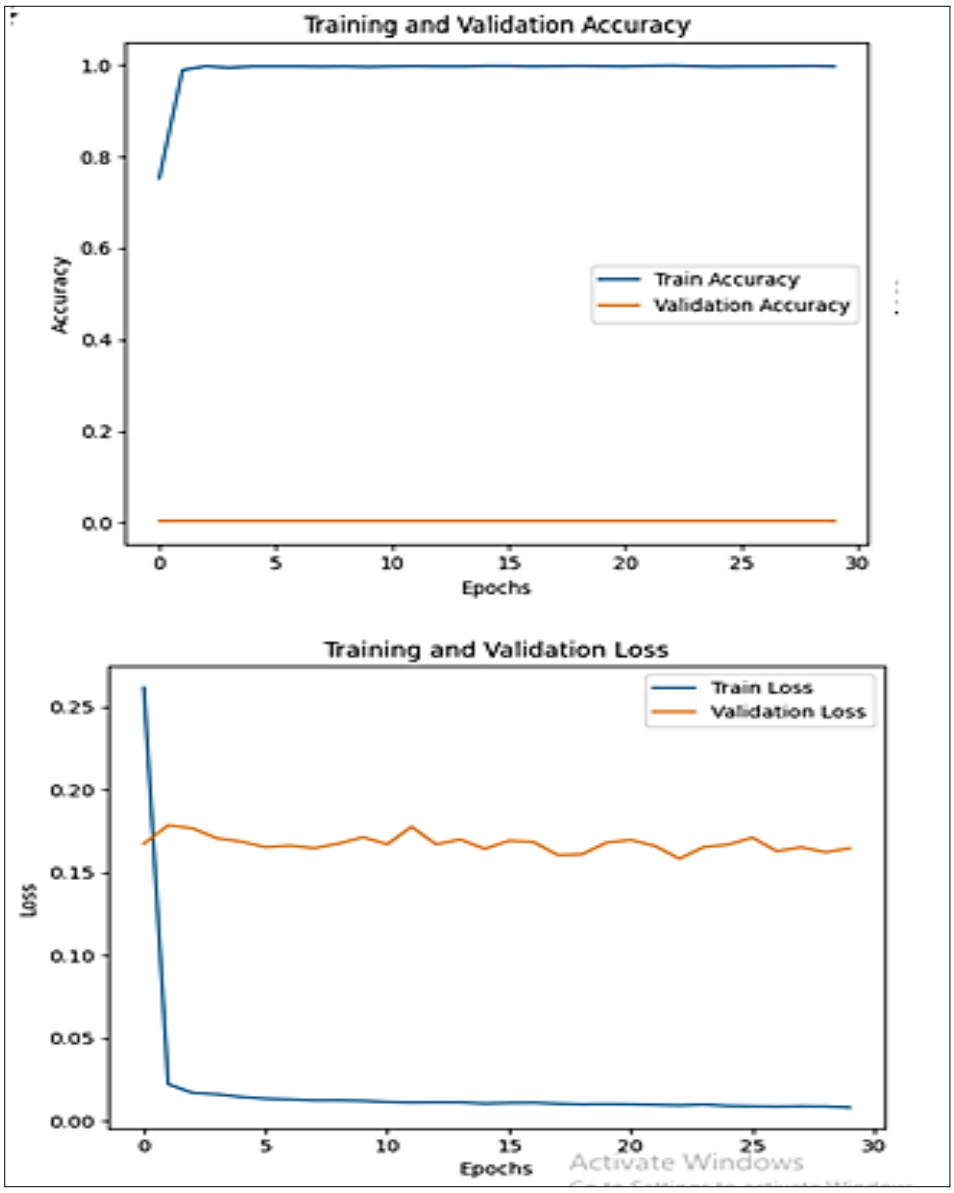

Fig 4: Training/ Validation Accuracy and loss graph

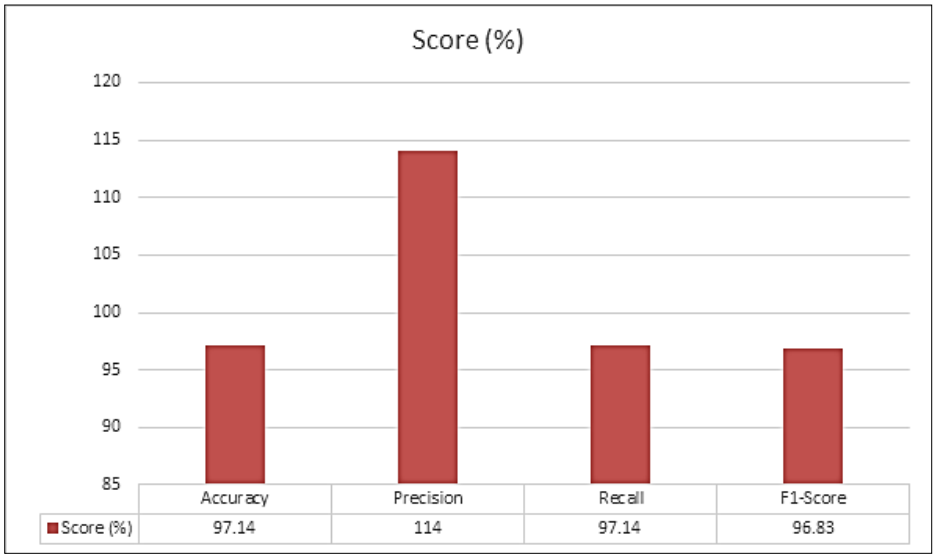

Fig 5: Performance evaluation of the system

In order to determine and analyze the performance of the hybrid algorithm for improving recognition system in human activities, key evaluation metrics which includes accuracy, precision, recall, and f1-score were used. The algorithm was

tested on data obtained from the UCF Crime Dataset repository, yielding results accuracy of 97.14%, a recall of 97.14%, an F1-Score of 96.83%, and a precision of 114.2%. From these metrics, it has shown that the hybrid algorithms presented a better performance than a single algorithm.

Table 1: Model cumulative evaluation table

SN	Evaluation Metrics	Score	(%)
1	Accuracy	0.09714	97.14
2	Precision	0.1142	114.2
3	Recall	0.09714	97.14
4	F1-Score	0.09683	96.83

4.3. System Requirements

A system is fundamentally a collection of interrelated and interdependent components that operate collectively to accomplish specific goals. Identifying these essential components is crucial as they directly impact the performance and functionality of the new system. The components required for the system to operate effectively are referred to as system requirements. These requirements must be specified with precision to ensure this hybrid algorithm does not only meet the required standards but also has the capacity to process the relevant data. System requirements can be categorized into the following:

A. Hardware requirement

- The basic requirement for this component should be Intel Core i7 10th generation processor with a minimum 3.3 GHz speed or higher with advanced micro devices processor AMD FX-4300 with 4.7 GHz can also suffice.
- The minimum requirement is between 4GB to 8GB RAM or higher, (HDD/ SSD) a minimum of 320GB to 500GB and display/monitor should be Intel(R) HD Graphics 3000 or higher.

B. Software requirement: The recommended operating environment for this hybrid algorithm includes Windows 10 or later, along with the Anaconda Python integrated development environment, and tools such as TensorFlow, Keras, and Jupyter Notebook.

5. Summary and Conclusion

With the rapid advancement of computer technologies, machine learning and AI, the landscape of security and surveillance has seen transformative improvements, making the protection of society more critical than ever. The integration of computer vision and image classification technologies has notably enhanced surveillance systems, offering higher accuracy and precision in detecting potential security threats. In today's world, security issues should not be the responsibility of governments alone but also of every member of society, as it plays a crucial role in sustainable development. A secure environment is foundational for growth, as insecurity can severely hinder progress. Therefore, it is of great importance to develop improved algorithms and models systems that can bolster security surveillance and provide early warning mechanisms to mitigate threats and alert law enforcement agencies are paramount.

The advancement of deep learning technologies has opened up new frontiers in crime detection and mitigation, particularly through computer vision and image recognition techniques. This system is a hybrid algorithm that combines convolutional neural networks with fuzzy logic algorithms, designed for human activity recognition. The model utilizes datasets extracted from the UCF crime dataset and incorporates a pre-trained VGG16 CNN model integrated with a support vector machine for optimal activity classification. It had a remarkable performance metrics as follows; an accuracy of 97.14%, a recall of 97.14%, an F1-Score of 96.83%, and a precision of 114.2%. Furthermore, when compared with existing models, the hybrid algorithm outperformed them, demonstrating a better output in the early detection of security threats within environments monitored by CCTV video streams.

6. Reference

1. Singh R, Kushwaha AKS, Chandni J, Srivastava J. Recent trends in human activity recognition – A comparative study. Cognitive Systems Research. 2023;77(1):30-44.
2. Li C, Zhang B, Chen C, Ye Q, Han J, Guo G, et al. Deep manifold structure transfer for action recognition. IEEE Transactions on Image Processing. 2019;28(9):4646-58. https://doi.org/10.1109/TIP.2019.2912357
3. Anazia EK, Adigwe W. IoT enabled smart house system using wi-fi technology. International Journal of Innovative Science and Research Technology. 2022;7(8):590. ISSN No:2456-2165.
4. Li Y, Liu C, Ji Y, Gong S, Xu H. Spatio-temporal deep residual network with hierarchical attentions for video event recognition. ACM Transactions on Multimedia Computing, Communications and Applications. 2020;16(2s). https://doi.org/10.1145/3378026
5. Xiong X, Min W, Han Q, Wang Q, Zha C. Action recognition using action sequences optimization and two-stream 3d dilated neural network. Computational Intelligence and Neuroscience. 2022;2022. https://doi.org/10.1155/2022/6608448
6. Shapiro B, Fiebrink R, Norvig P. How machine learning impacts the undergraduate computing curriculum. Communications of the ACM. 2018;61(11):27-9.
7. Serpush F, Menhaj MB, Masoumi B, Karasfi B. Wearable sensor-based human activity recognition in the smart healthcare system. Computational Intelligence and Neuroscience. 2022;2022:1-31.
8. Anazia KE, Ojei EO, Ekibade OJ, Idama RO. An enhanced model for premium motor spirit (PMS) price prediction and management in Nigeria using machine learning. FUDMA Journal of Sciences. 2024;8(6). DOI: https://doi.org/10.33003/f js-2024-0806-2926
9. Diraco G, Rescio G, Siciliano P, Leone A. Review on human action recognition in smart living: Sensing technology, multimodality, real-time processing, interoperability, and resource-constrained processing. Sensors. 2023;23(11):5281.
10. Chukwudi JC, Omede GC, Edje A, Anazia EK. Database security system using dynamic time-warping voice recognition authentication. International Journal of Scientific Research and Engineering Development. 2024;7(2).

11. Beddiar DR, Nini B, Sabokrou M, Sabokrou M, Hadid A. Vision-based human activity recognition: a survey. Multimedia Tools and Applications. 2020;79(1):30509-55.
12. Gupta N, Gupta SK, Pathak RK, Jain V, Rashidi P, Suri JS. Human activity recognition in artificial intelligence framework: a narrative review. Artificial Intelligence Review. 2022;55(1):4755-808.
13. Ranasinghe S, Al Machot F, Mayr HC. A review on applications of activity recognition systems with regard to performance and evaluation. International Journal of Distributed Sensor Networks. 2016;12(8):1-22.
14. Botta A, De Donato W, Persico V, Pescapé A. Integration of cloud computing and internet of things: A survey. Future Generation Computing Systems. 2016;56(1):684-700. doi:10.1016/j.future.2015.09.021
15. Weiss GM, Yoneda K, Hayajneh T. Smartphone and smartwatch-based biometrics using activities of daily living. IEEE Access. 2019;7(1):133190-202.
16. Anazia EK, Ojei E, Okpor MD. A fuzzy logic-based automobile fault detection system using mamdani algorithm. International Journal of Scientific Research and Management. 2024;12(3):1081-93. DOI: 10.18535/ijsrm/v12i03.ec06.
17. Kwon M, Choi S. Recognition of daily human activity using an artificial neural network and smartwatch. Wireless Communications and Mobile Computing. 2018;2018:1-9.
18. Ding X, Yang K, Chen W. An attention-enhanced recurrent graph convolutional network for skeleton-based action recognition. ACM International Conference Proceeding Series. 2019:79-84.
19. Murad A, Pyun J. Deep recurrent neural networks for human activity Recognition. Sensors. 2017;17(11):2556-69.
20. Qin Z, Qin Z, Meng S, Qin Z, Choo KR. Imaging and fusing time series for wearable sensor-based human activity recognition. Information Fusion. 2020;53(1):80-7.
21. Sansano E, Montoliu R, Belmonte FÓ. A study of deep neural networks for human activity recognition. Computational Intelligence. 2020;36(3):1113-39.
22. Mliki H, Bouhlel F, Hammami M. Human activity recognition from UAV-captured video sequences. Pattern Recognition. 2020;100(1):140-50.
23. Wu H, Ma X, Li Y. Multi-level channel attention excitation network for human action recognition in videos. Signal Processing: Image Communication. 2023;114(1):116940.
24. Song S, Chandrasekhar V, Mandal B, Li L, Lim J, Babu GS, et al. Multimodal multi-stream deep learning for egocentric activity recognition. IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). 2016:378-85.
25. Liu L, Shao L, Li X, Lu K. Learning spatio-temporal representations for action recognition: a genetic programming approach. IEEE Transactions on Cybernetics. 2016;46(1):158-70.
26. Attal F, Mohammed S, Dedabrishvili M, Chamroukhi F, Oukhellou L, Amirat Y. Physical human activity recognition using wearable sensors. Sensors. 2015;15(12):31314-38.
27. Mohmed G, Lotfi A, Pourabdollah A. Human activities recognition based on neuro-fuzzy finite state machine. Technologies. 2018;6(4):110-20.
28. Ferro E, Lazzeri A, Palumbo F, Vaglini G. Monitoring elderly behavior via indoor position-based stigmergy. Pervasive and Mobile Computing. 2015;23(1):26-42.
29. Anwer F, Aftab S, Waheed U, Muhammad SS. Agile software development models TDD, FDD, DSDM, and crystal methods: a survey. International Journal of Multidisciplinary Science and Engineering. 2017;8(2):1-10.
30. Athavale VA, Gupta SC, Kumar D, Savita S. Human action recognition using CNN-SVM model. Advances in Science and Technology. 2021;105(1):282-90.
31. Sasakawa D, Honma N, Nakayama T, Iizuka S. Human activity identification by height and doppler RCS information detected by MIMO Radar. IEICE Transactions on Communications. 2019;102(7):1270-8.
32. Okpor MD, Anazia EK, Ukpnusiowho D. A novel hybrid database security management technique. International Journal of Science and Research Archive. 2024. ISSN: 2582-8185.
33. Inyiama HC, Anazia EK. Enhanced big data veracity classification using neutrosophic logic and neural network. International Journal of Scientific & Engineering Research. 2020;11(2):100. ISSN: 2229-5518.
34. Gupta N, Gupta SK, Pathak RK, Jain V, Rashidi P, Suri JS. Human activity recognition in artificial intelligence framework: a narrative review. Artificial Intelligence Review. 2022;55(1):4755-808.
35. Hussain Z, Sheng M, Zhang WE. Different approaches for human activity recognition: A survey. SoftwareX. 2019:1-28.
36. Aktas E. A machine learning application for classification of human activity recognition in IoT [dissertation]. Dublin: Dublin Business School; 2018.
37. Okofu S, Anazia EK, Akazue M, Ogeh C, Ajenaghughrure IB. The interplay between trust in human-like technologies and integral emotions: Google assistant. KZYJC Journal Publications. 2023;38(1). ISSN: 1001-0920.
38. Ambrosin M, Anzanpour A, Conti M, Dargahi T, Moosavi SR, Rahmani AM, et al. On the Feasibility of attribute-based encryption on internet of things devices. IEEE Micro. 2016;36(6):25-35.