Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

RESEARCH ARTICLE

Abnormal Event Detection and Signaling in Multiple Video Surveillance Scenes Using CNN

Neetu Vijayananda. Lavanya N L . Nidhi N Sattigeri . Nisarga R K . Pooja N M

Computer Science and Engineering Department,
Sapthagiri College of engineering, Karnataka, India

Received: 07 April 2023 / Revised: 22 April 2023 / Accepted: 3 May 2023

DOI: 10.5281/zenodo.7937890

Abstract – Computer vision's key duty of abnormal situation identification has applications in surveillance, anomaly monitoring, and industrial inspection. This presentation offers a summary of the methods and developments in abnormal event detection with a particular emphasis on the application of Convolutional Neural Networks (CNNs). In a variety of computer vision applications, such as object detection and picture categorization, CNNs have achieved astounding success. CNNs have been widely used for abnormal event detection because of their capacity to extract hierarchical and spatial characteristics. CNN models may learn to distinguish between normal and abnormal patterns by being trained on huge datasets of typical occurrences. This allows for efficient anomaly identification. The effectiveness of CNN-based abnormal event detection has been greatly enhanced via transfer learning. For specialized abnormal event detection applications, pre-trained CNN models, like those trained on ImageNet, offer a foundation of learnt characteristics that may be fine-tuned. The model's capacity to generalize to new datasets and previously undiscovered anomalies is improved by this transfer of information.

Index Terms – Convolutional Neural Network, Abnormal Event, Pooling Layer, Classification, Sequential model, Back Propagation.

I. INTRODUCTION

Since the topics in computer vision such as visual saliency, interestingness prediction, dominant behavior detection, and others, abnormal event detection in intelligent tape has attracted increasing attention from academic and industrial communities in recent years. Due to the ambiguous concepts of normalcy and abnormalities and the reliance of the dentitions on the background situation, abnormal event

Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

identification for video sequences is a challenging task. However, it may be said that anomalous conduct or activity brought on by unexpected occurrences happens less frequently than typical (known) situations. Multiple modelling methods are suggested in the literature for identifying abnormal situations in surveillance videos, including trajectory-based models, spatiotemporal feature-based models, and sparse reconstruction-based models. However, the majority of these approaches focus on learning and extracting deep or hand-crafted video appearance features from given samples, classifying the features to determine whether the events are abnormal if they deviate from the norm.

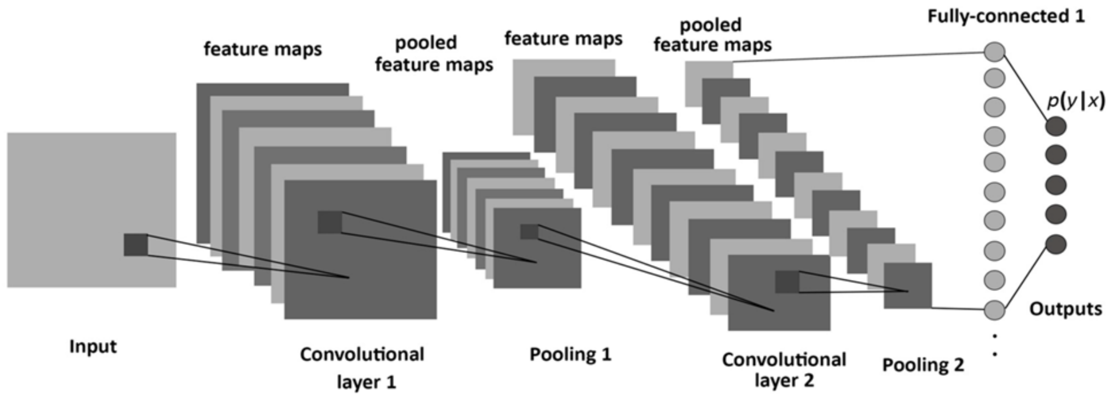

Fig 1: The Convolutional Neural Network

II. BACKGROUND

The history of abnormal event detection is closely intertwined with the development of computer vision and pattern recognition techniques. Here is an overview of key milestones and developments in the field. Early Approaches, In the 1990s, researchers focused on simple rule-based methods for abnormal event detection. These approaches relied on handcrafted features and thresholds to identify deviations from normal patterns. Background modeling techniques were introduced to distinguish foreground objects from the background in surveillance videos. Changes or anomalies in the foreground regions were considered as abnormal events. Statistical Methods, Statistical modeling played a significant role in early abnormal event detection. Methods such as Gaussian Mixture Models (GMMs) and Hidden Markov Models (HMMs) were employed to learn the statistical properties of normal events and detect deviations. These techniques were effective for relatively simple scenarios but struggled with complex scenes and variations in lighting conditions.

Anomaly Detection in Machine Learning, Anomaly detection algorithms gained popularity in various domains, including computer vision. These techniques aimed to identify rare or abnormal patterns in data without relying on explicit modeling of normal behavior. Unsupervised learning methods, such as clustering-based approaches (e.g., k-means) and density estimation techniques (e.g., Local Outlier Factor), were used for abnormal event detection.

Motion-based Approaches, Motion-based abnormal event detection became prominent with the introduction of motion analysis techniques. Optical flow methods were used to capture motion patterns in videos and detect anomalies based on unexpected or abnormal motion behavior. Spatiotemporal modeling, such as using 3D tensors or spatiotemporal volumes, was employed to analyze the motion patterns over time.

Deep Learning Revolution, the advent of deep learning, particularly Convolutional Neural Networks (CNNs), brought significant advancements to abnormal event detection. CNNs demonstrated excellent performance in tasks like object recognition and image classification, which led researchers to explore their potential in abnormal event detection. CNNs were utilized for feature extraction and learning discriminative representations from data, allowing the detection of complex and subtle abnormalities. The history of abnormal event detection demonstrates a shift from rule-based and statistical methods to the emergence of deep learning and advanced techniques capable of capturing complex patterns and temporal dependencies. The field continues to evolve as researchers address challenges related to data scarcity, model generalization, real-time processing, and interpretability

III. PROBLEM STATEMENT

Even with servlets cameras, it might be difficult for a person to monitor odd occurrences like chain theft and attempted murder in a big city. So, a system that classifies occurrences as normal or abnormal using machine learning approaches is now being developed. If the incidence is unusual, a warning message will be delivered to the appropriate department. The objective is to develop a computer system or algorithm that, given a set of events or observations, can automatically identify and classify anomalous occurrences or events that are out of the norm. Abnormal events are those that drastically deviate from the expected or typical patterns, behaviours, or attributes included in the dataset. Depending on the requirements of the application, the system should be able to detect anomalies either offline or in real-time.

IV. SYSTEM DESIGN

System design involves defining the architecture, components, modules, interfaces, and other characteristics of a system to meet specific requirements and objectives. It involves transforming requirements into a detailed blueprint that outlines how the system will be structured, organized, and implemented. In system design, various elements are considered and addressed to ensure the system's effectiveness, efficiency, reliability, maintainability, and scalability. The Fig.2 gives us an idea of the working of the system, we begin by collecting the data from the CCTV Surveillance and then we go ahead to process these videos by splitting them into frames, each frame is scaled and normalized as they might be distorted and may cause problems during the training phase. After the processing of the frame is done, we then extract the feature using the feature vector and split the frames into training and testing set, which is usually in the ratio of 80:20. After the training of the model using CNN algorithm, we then evaluate the model with respect to its accuracy, performance and reliability in the real world. The final step is the deployment of the model in the real world.

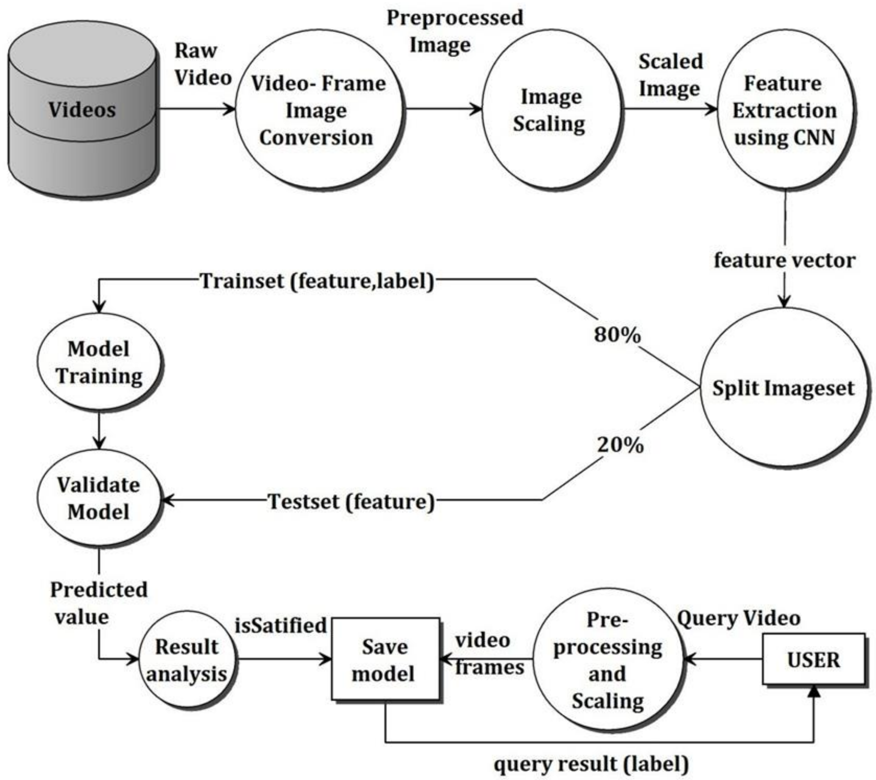

Fig 2. Dataflow Diagram

V. SYSTEM IMPLEMENTATION

System implementation in the context of abnormal event detection involves deploying the trained model and integrating it into a working system. Here's an overview of the steps involved in system implementation but the first step is to define System Requirements, clearly identifying the requirements and objectives of the abnormal event detection system. Consider factors such as the input data sources (e.g., video streams, sensor data), real-time or offline processing, desired output format (e.g., visual alerts, notifications), and any specific constraints or performance criteria.

Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

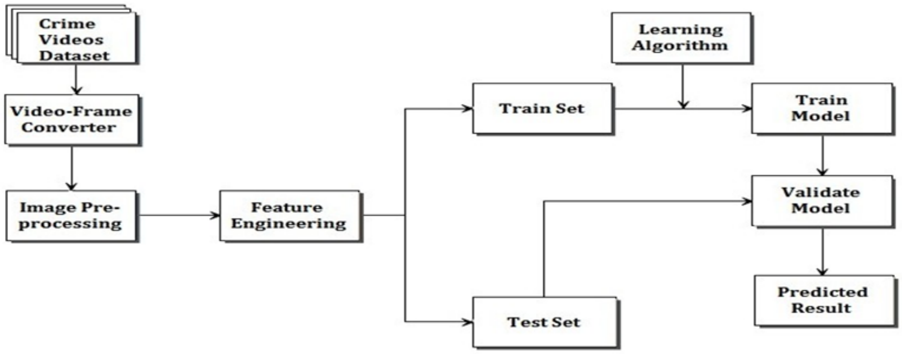

Fig 3. System Architecture

Data Collection

Data collection is essential to abnormal event detection since it helps to gather pertinent details about the system or environment that is being watched. Depending on the application and the type of anomalous occurrences being recognised, different techniques and sources of data may be used. Here are a few typical methods for gathering data: sensor networks, log files, internet of things (IoT) devices, and video surveillance. We concentrate on and further process the data gathered from the CCTV Surveillance in our project.

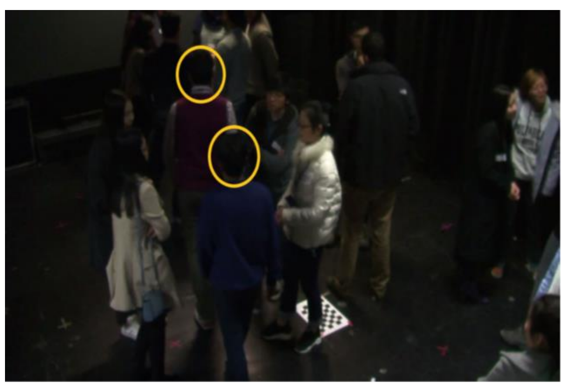

Fig 3. Data collected through CCTV Surveillance

Image Acquisition and Preprocessing

In abnormal event detection systems that analyze images, the process typically involves image acquisition and preprocessing. Here's an overall understanding of image acquisition and preprocessing steps in abnormal event detection:

Image Acquisition: Images can be taken from different sources, such as surveillance cameras, drones, or other imaging devices. The cameras or devices may be strategically placed to cover the area of interest, capturing a continuous stream of images or individual frames at specific time intervals.

Image Preprocessing: Once the images are acquired, preprocessing techniques are applied to enhance the quality of the images and extract relevant features. Some common preprocessing steps include:

- Image Resizing and Scaling: Images may need to be resized or scaled to a consistent resolution for efficient processing. This phase gaurentees that all images have the same dimensions, which can be important for subsequent analysis.
- Noise Reduction: Noise can be introduced during the image acquisition process. Techniques such as Gaussian or median filtering can be applied to remove noise and improve the overall image quality.
- Contrast Enhancement: Enhancing image contrast can help highlight important details and make anomalies more distinguishable. Techniques like histogram equalization or adaptive histogram equalization can be used to enhance the contrast of the images.
- Image Normalization: Image normalization techniques can be applied to standardize the image data. This can involve adjusting the image intensity levels, applying color space transformations, or normalizing pixel values to a specific range.
- Feature Extraction: In abnormal event detection, this is a crucial step. Various methods can be used to extract relevant features from the preprocessed images. These features can include color histograms, texture descriptors (e.g., Gabor filters, Local Binary Patterns), edge or contour information, or higher-level features extracted using deep learning models (e.g., convolutional neural networks).
- Dimensionality Reduction: In cases where the extracted features are high-dimensional, dimensionality reduction techniques (e.g., Principal Component Analysis, t-SNE) can be applied to decrease the feature space's dimensionality while retaining the most informative features.
- Normalization: Feature normalization is often applied to ensure that the features are on a similar scale, which can help in the subsequent modeling and anomaly detection steps.

The specific preprocessing techniques and steps can differ depending on the characteristics of the images, the domain, and the abnormal events of interest. The goal of image acquisition and preprocessing is to better the quality of the images, enhance relevant features, and prepare the data for subsequent abnormal event detection algorithm.

Data Preparation and Model Construction

Once the data has been acquired and preprocessed, it needs to be prepared in a suitable format for model construction. Here are some steps involved in data preparation for abnormal event detection:

- Splitting the Data: The preprocessed data is typically divided into training, validation, and testing sets. The training set is used to train the model, the validation set is used for hyperparameter tuning and model selection, and the testing set is used to evaluate the final model's performance.
- Labeling: The data needs to be labeled to indicate whether each instance represents a normal or abnormal event. Labeling can be done manually by domain experts or automated if annotated data is available. The labeled data is used for training and evaluating the abnormal event detection model.
- Balancing the Data: Depending on the distribution of normal and abnormal events in the dataset, it might be necessary to balance the data to ensure that the model is not biased towards the majority class. Techniques such as oversampling or undersampling can be used to achieve a balanced dataset.
- Feature Selection/Extraction: If the preprocessed data has a lot of features, it could be helpful to perform feature selection to find the ones that are most useful. Reduce dimensionality and concentrate on the most important features of the data with the use of feature selection algorithms. Alternately, the data can be transformed into a more condensed and useful representation using feature extraction algorithms.
- Model Construction: After the data has been prepared, the next step is to construct a model that can effectively detect abnormal events. We are utilising a convolutional neural network to generate our model. Yann LeCun first suggested convolutional neural networks (CNN) in 1988 as a unique design for artificial neural networks. Some visual cortex properties are used by CNN. After completing the pre-processing, we can begin putting our neural network into practise. We're going to use 2 x 2 max-pooling on 3 convolution layers.

Max-pooling: A method for reducing the size of an image that involves taking the maximum pixel value from a grid. Additionally, it lessens over fitting and broadens the model's applicability. We then add two completely linked layers after that. We require a flattening layer between completely linked layers since their input should be two dimensional and their output should be four dimensional. A softmax layer is located at the very end of the completely linked layers.

Model Training

Model training using Convolutional Neural Networks (CNNs) for abnormal event detection involves the following steps, Initialize the Model: Initialize the CNN model with the dataset. We divide the dataset into Train and Test initially. The model is then successively trained and validated on these various sets, setting aside the Test set in the process. Instead, they randomly select X% of their Train dataset to be the true Train set, and the remaining (100-X) % to be the Validation set, where X is a fixed value (say, 80%). So, in order to prepare data for the training and testing phases, we will use the same procedure.

MILESTONE RESEARCH FOUNDATION
Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

Training Loop: Iterate through the training set for a fixed number of epochs or until convergence. In each epoch:

- Forward Propagation: Pass the training data through the layers of the CNN model in a forward direction, producing predicted outputs.
- Calculate Loss: Compare the predicted outputs with the true labels and compute the loss using the selected loss function.
- Backpropagation: Perform backpropagation to calculate the gradients of the loss with respect to the model's weights.
- Update Weights: Use the chosen optimization algorithm to update the model's weights depends on the computed gradients.

Model Training is the most significant step in the system architecture and the entire accuracy, performance of the model depends on this phase.

Model Testing and Evaluation

The construction of an abnormal event detection system must go through critical stages such as model testing and evaluation. These actions assist in evaluating the trained model's effectiveness and performance in identifying anomalous events. An outline of the model testing and evaluation procedure is provided below:

- Evaluation Criteria: In order to evaluate the performance of the model, we employ suitable assessment metrics. Accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC-ROC), and area under the precision-recall curve (AUC-PR) are common measures for abnormal event identification. Metrics are selected based on the problem's unique requirements and characteristics.
- Performance Metrics: Compare the model's predictions with the true labels from the test dataset and calculate the selected evaluation metrics. These numbers provide quantitative study of how good the model is detecting abnormal events.
- Visualize Results: Visualize the model's performance using various techniques such as confusion matrices, precision-recall curves, ROC curves, or detection error tradeoff (DET) curves. Visualizations help in understanding the model's behavior and its trade-off between true positive and false positive rates.
- Interpret Performance Metrics: Analyze the calculated performance metrics and visualizations to gain insights into the model's strengths and weaknesses. Understand how the model is performing in terms of correctly identifying abnormal events and minimizing false positives or false negatives.
- Fine-tuning and Model Iteration: If the model's performance is not satisfactory, consider fine-tuning the model by adjusting hyperparameters, modifying the architecture, or incorporating

additional features or data. Iterate on the training and evaluation process to improve the model's performance.

- Comparison with Baselines: Compare the model's performance with baseline methods or existing approaches in the field. This comparison helps assess the model's effectiveness and understand its performance against other solutions.
- Consider Real-world Implications: Evaluate the model's performance in the context of real-world deployment. Consider different factors such as computational efficiency, scalability, interpretability, and robustness to different environmental conditions.

VI. DISCUSSION

Abnormal event detection using Convolutional Neural Networks (CNNs) has proven to be a versatile and effective approach in computer vision tasks. CNNs have the ability to learn and extract significant features from dataset, making them well-suited for detecting and classifying abnormal events in various domains. Main key advantages of using CNNs for abnormal event detection is their capability to capture spatial information. CNNs excel at analyzing visual data such as images and videos, enabling them to identify patterns and anomalies based upon the arrangement and relationships of pixels or regions within the data. Furthermore, CNNs are able to learn complex representations of data through hierarchical feature extraction. This allows them to identify and differentiate subtle variations and deviations from normal behavior that might be challenging for traditional methods or human observers. Transfer learning has significantly enhanced the performance of CNNs in abnormal event detection. Pretrained CNN models, trained on large-scale datasets such as ImageNet, provide a foundation of general knowledge that can be fine-tuned for specific abnormal event detection tasks. This enables the models to leverage the learned representations and generalize well to new datasets or domains. Attention mechanisms have been introduced to further improve the localization and identification of abnormal events. By focusing on salient regions or frames within the data, attention-based CNN models can effectively highlight and detect anomalies, providing valuable information for subsequent analysis or action.

However, there are few limitations and challenges to consider. The availability of labeled abnormal training data can be limited, which hinders the training process and generalization to unseen anomalies. Class imbalance, where abnormal events are rare compared to normal events, can also pose challenges in model training and performance evaluation. Precise localization of abnormal events within the data is another area of concern. While CNNs are proficient at identifying anomalies, determining the exact location or extent of the abnormality can be challenging. Additional post-processing techniques or specialized architectures are often required to achieve precise localization. The computational complexity of CNNs is also a consideration, particularly for real-time or resource-constrained applications. CNN models can be computationally intensive, requiring substantial processing power and memory. Efficient model architectures and better techniques are ceaselessly being developed to address these concerns

Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

VII. CONCLUSIONS

In conclusion, abnormal event detection using Convolutional Neural Networks (CNNs) has emerged as a powerful technique in computer vision for identifying and classifying abnormal situations in videos or image sequences. CNNs have shown significant potential in capturing spatial and temporal patterns, allowing for accurate anomaly situation detection in various domains such as surveillance, industrial monitoring, and healthcare. By training CNN models on large datasets of normal events, they can learn to extract important features and patterns that represent the expected behavior. These models can then effectively distinguish abnormal situation that differ from the learned normal patterns. The use of transfer learning, pretrained models, and attention mechanisms has further improved the performance of CNNs in abnormal situation detection tasks.

REFERENCES

1. Lu, C., Shi, J., & Jia, J. (2013). Abnormal event detection at 150 fps in matlab. In Proceedings of the IEEE international conference on computer vision (pp. 2720-2727).
2. Del Giorno, A., Bagnell, J. A., & Hebert, M. (2016). A discriminative framework for anomaly detection in large videos. In Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part V 14 (pp. 334-349). Springer International Publishing.
3. Atghaei, A., Ziaeinejad, S., & Rahmati, M. (2020). Abnormal event detection in urban surveillance videos using GAN and transfer learning. arXiv preprint arXiv:2011.09619.
4. Ma, Q. (2021). Abnormal Event Detection in Videos Based on Deep Neural Networks. Scientific Programming, 2021, 1-8.
5. Javan Roshtkhari, M., & Levine, M. D. (2013). Online dominant and anomalous behavior detection in videos. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2611-2618).
6. Ramachandra, B., & Jones, M. (2020). Street scene: A new dataset and evaluation protocol for video anomaly detection. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (pp. 2569-2578).
7. Sultani, W., Chen, C., & Shah, M. (2018). Real-world anomaly detection in surveillance videos. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 6479-6488).
8. Madhusudhan, M. V., Udaya Rani, V., & Hegde, C. (2021). Finger vein recognition model for biometric authentication using intelligent deep learning. *International Journal of Image and Graphics*, 2240004.
9. Herzig, R., Levi, E., Xu, H., Gao, H., Brosh, E., Wang, X., ... & Darrell, T. (2019). Spatio-temporal action graph networks. In Proceedings of the IEEE/CVF international conference on computer vision workshops.
10. Haresh, S., Kumar, S., Zia, M. Z., & Tran, Q. H. (2020, October). Towards anomaly detection in dashcam videos. In 2020 IEEE Intelligent Vehicles Symposium (IV) (pp. 1407-1414). IEEE.
11. Chattoraj, M., & Vinayakamurthy, U. R. (2021). A self adaptive new crossover operator to improve the efficiency of the genetic algorithm to find the shortest path. *Indonesian Journal of Electrical Engineering and Computer Science*, *23*(2), 1011-1011.
12. Al-Shammari, N. K., Alzamil, A. A., Albadarn, M., Ahmed, S. A., Syed, M. B., Alshammari, A. S., & Gabr, A. M. (2021). Cardiac stroke prediction framework using hybrid optimization algorithm under DNN. *Engineering, Technology & Applied Science Research*, *11*(4), 7436-7441.
13. Sreedhar Kumar, S., Ahmed, S. T., Mercy Flora, P., Hemanth, L. S., Aishwarya, J., GopalNaik, R., & Fathima, A. (2021, January). An Improved Approach of Unstructured Text Document Classification Using Predetermined Text Model and Probability Technique. In *ICASISET 2020: Proceedings of the First International Conference on Advanced*

Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

Scientific Innovation in Science, Engineering and Technology, ICASISET 2020, 16-17 May 2020, Chennai, India (p. 378). European Alliance for Innovation.

14. Morais, R., Le, V., Tran, T., Saha, B., Mansour, M., & Venkatesh, S. (2019). Learning regularity in skeleton trajectories for anomaly detection in videos. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 11996-12004).
15. Ahmed, S., Guptha, N., Fathima, A., & Ashwini, S. (2021, January). Multi-View Feature Clustering Technique for Detection and Classification of Human Actions. In *Proceedings of the First International Conference on Advanced Scientific Innovation in Science, Engineering and Technology, ICASISET 2020, 16-17 May 2020, Chennai, India*.
16. Bhat, A., Bhanuranjan, S. B., Narayan, K. L., & Lavanya, N. L. (2023). Survey On Object Detection, Face Tracking, Digital Mapping and Lane Following For Remotely Piloted Aerial Systems (RPAS). International Journal of Human Computations & Intelligence, 2(2), 94-105.