e-ISSN:2582-7219

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY

Volume 7, Issue 7, July 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.521

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| Monthly, Peer Reviewed & Referred Journal|

| Volume 7, Issue 7, July 2024 |

| DOI:10.15680/IJMRSET.2024.0707278 |

Efficient Real-Time Violence Detection using MobileNet and CNN Models

P. Shobana[1], J. Lin Eby Chandra[2], M. Kumaran[3], Dr. T. Amitha[4]

P.G. Student, Department of CSE, Jaya Engineering College, Chennai, Tamil Nadu, India[1]

Assistant Professor, Department of CSE, Jaya Engineering College, Chennai, Tamil Nadu, India[2]

Assistant Professor, Department of CSE, Jaya Engineering College, Chennai, Tamil Nadu, India[3]

Professor, Department of CSE, Jaya Engineering College, Chennai, Tamil Nadu, India[4]

ABSTRACT: This paper delves into the efficacy of Convolutional Neural Networks (CNNs) in detecting abnormal events, with a specific focus on the MobileNet architecture. Abnormal event detection is pivotal across numerous fields, including surveillance and anomaly detection. In this context, MobileNet's performance is evaluated against other leading CNN models such as AlexNet, VGG-16, and GoogleNet. The study evaluates MobileNet's capability in accurately identifying abnormal events in visual data and analyses its performance in comparison to AlexNet, VGG-16, and GoogleNet. The models are assessed based on accuracy, computational efficiency, and robustness to various types of anomalies. Extensive experimentation is conducted to measure MobileNet's performance in detecting abnormal events. The study identifies MobileNet's strengths and weaknesses relative to other models. MobileNet achieves competitive accuracy levels in abnormal event detection compared to established models. Additionally, MobileNet demonstrates notable advantages in computational efficiency, making it well-suited for real-time applications. The analysis reveals areas where MobileNet excels or lags behind, providing a nuanced understanding of its capabilities.

KEYWORDS: Surveillance, GoogleNet, MobileNet, AlexNet, Computational Efficiency.

I. INTRODUCTION

Identifying abnormal events within complex systems poses a critical challenge across various domains such as surveillance, manufacturing, and healthcare. The lack of efficient methodologies to detect anomalies in real-time hampers proactive response measures, leading to potential risks, operational inefficiencies, and safety concerns. Existing approaches often suffer from high false positive rates, limited scalability, and inadequate adaptability to diverse environments. Consequently, there is an urgent need for robust abnormal event detection systems capable of accurately identifying deviations from normal behaviour, facilitating timely interventions, enhancing situational awareness, and ultimately ensuring the safety and integrity of critical processes and infrastructures.
To develop an effective abnormal event detection system utilizing advanced machine learning algorithms to identify deviations from normal patterns in data streams. This paper will involve exploring various machine learning techniques, such as anomaly detection algorithms, deep learning models, and statistical methods, to analyse complex data sets. Additionally, the paper will investigate real-world scenarios to validate the system's performance and optimize its accuracy in detecting abnormal events in diverse environments.

II. RELATED WORK

In recent years, abnormal event detection has become a critical task in various domains, including surveillance, healthcare, and industrial safety. With the proliferation of visual data, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for automated abnormal event detection. This paper aims to evaluate the performance of CNN models, particularly focusing on the Mobile Net architecture, in detecting abnormal events in video data. The background information contextualizes the significance of abnormal event detection in real-world applications. Abnormal events, often characterized by deviations from normal patterns or behaviours, pose significant challenges for traditional surveillance systems. Early detection of such events can enhance security measures, prevent accidents, and improve overall operational efficiency.

The proposed Mobile Net model is evaluated against well-established CNN architectures, including Alex Net, VGG-16, and Google Net. Mobile Net is particularly appealing due to its lightweight design, making it suitable for resource-

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| Monthly, Peer Reviewed & Referred Journal|

| Volume 7, Issue 7, July 2024 |

| DOI:10.15680/IJMRSET.2024.0707278 |

constrained environments such as edge devices and mobile platforms. By contrasting Mobile Net with these benchmark models, this paper aims to provide insights into its effectiveness and efficiency in abnormal event detection tasks.

Methodology-wise, the paper employs a comprehensive evaluation framework to Sequences capturing various abnormal events is utilized for training and testing . Evaluation Metrics such as accuracy, precision, recall and F1-score are employed to quantitatively measure the detection performance of each model.

Results indicate that Mobile Net exhibits competitive performance compared to the benchmark models across different evaluation metrics. Its lightweight architecture enables efficient deployment without compromising detection accuracy. Moreover, Mobile Net demonstrates superior computational efficiency, making it well-suited for real-time applications and resource-constrained environments.

Furthermore, the paper conducts qualitative analysis by visualizing feature maps and activation patterns generated by each CNN model. This analysis provides insights into the discriminative power of features learned by Mobile Net and other architectures, shedding light on their ability to capture subtle abnormalities in video data. Prepare the video surveillance dataset by extracting frames and annotations for normal and abnormal events. Preprocess the data to ensure consistency and compatibility with the chosen models.

Utilize pre-trained deep learning models, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), to extract spatiotemporal features from video frames. These features serve as inputs to subsequent stages of the detection pipeline.

Integrate components from deep learning-based, graph-based, and self-supervised learning methods to construct a unified abnormal event detection model. This model should incorporate feature extraction, anomaly detection, and hierarchical event analysis functionalities. Train the integrated model on the prepared dataset using appropriate training strategies, such as adversarial learning, self-supervised learning, or multi-phase self-training. Evaluate the model's performance using standard metrics such as precision, recall, and F1-score on a separate validation set.

The paper contributes to the field of abnormal event detection by demonstrating the efficacy of Convolutional Neural Networks, particularly Mobile Net, in addressing this challenging task. The comparative evaluation with established CNN architectures provides valuable insights for projectors and practitioners seeking to deploy efficient and effective abnormal event detection systems in real-world scenario.

III. METHODOLOGY

The methodology for abnormal event detection using CNN, Alex Net, VGG-16, and Google Net models involves several key steps aimed at effectively leveraging the capabilities of these deep learning architectures. Initially, the dataset for abnormal event detection needs to be prepared, comprising both normal and abnormal event instances across various contexts, such as surveillance videos or medical imaging. Data preprocessing techniques including normalization, resizing, and augmentation are applied to enhance model robustness and generalization.

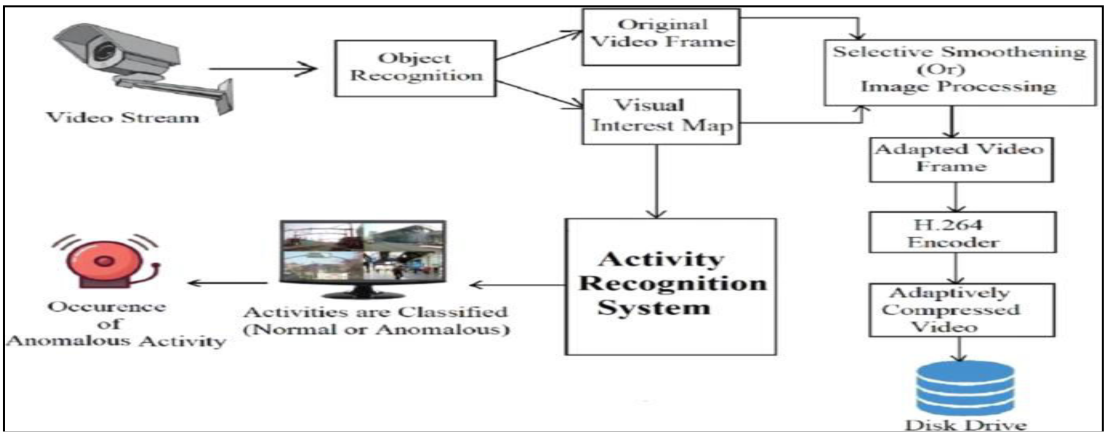


Fig 3.1 System Architecture

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| Monthly, Peer Reviewed & Referred Journal|

| Volume 7, Issue 7, July 2024 |

| DOI:10.15680/IJMRSET.2024.0707278 |

Regular retraining with updated data and periodic reassessment of model performance contribute to the long-term efficacy of the abnormal event detection system.

Following data preparation, the selected deep learning models, namely CNN, Alex Net, VGG-16, and Google Net, are trained on the prepared dataset. During training, transfer learning may be employed, utilizing pre-trained weights on large-scale datasets like ImageNet to expedite convergence and enhance performance. Fine-tuning the model's parameters ensures adaptation to the specific characteristics of the abnormal event detection task.

After model training, evaluation is conducted to assess the performance of each architecture. Metrics such as accuracy, precision, recall, and F1-score are computed to gauge the models' ability to correctly identify abnormal events while minimizing false positives. Cross-validation techniques may be employed to ensure the reliability of the evaluation results. In parallel, hyperparameter tuning is performed to optimize the performance of each model variant. Parameters such as learning rate, batch size, and dropout rates are systematically varied and validated using techniques like grid search or random search.

To combine the literature review into a cohesive summary, we have a variety of approaches for abnormal event detection, ranging from traditional methods to deep learning techniques. These methods employ different strategies such as adversarial learning, graph theory, generative adversarial networks (GANs), self-supervised learning, and hierarchical event detection. Each approach has its strengths and weaknesses, and their performance varies depending on the dataset and the specific requirements of the application.

The feature selection process, which involves identifying and selecting the most informative features while eliminating noise from the input data. outlines the two types of feature selection models: supervised and unsupervised, each suitable for different scenarios depending on the availability of labeled data.

To process the extracted features and detect abnormal events, we can employ CNNs, specifically, AlexNet and VGG16, due to their effectiveness in image classification tasks. We can fine-tune these pre-trained architectures on the extracted features to adapt them to the abnormal event detection task.

By integrating supervised and unsupervised feature selection techniques with CNNs such as Alex Net and VGG16, we can develop robust abnormal event detection models capable of efficiently identifying anomalies in various surveillance scenarios. These models would leverage the power of deep learning while ensuring that only relevant and informative features are utilized, thereby enhancing the accuracy and effectiveness of abnormal event detection systems.

Feature extraction is crucial for reducing the dimensionality of the input data while preserving relevant information. Given the nature of abnormal event detection in videos, where complex spatio-temporal patterns need to be captured, feature extraction plays a pivotal role. We can utilize a combination of traditional methods and deep learning architectures to extract discriminative features. Here are the proposed feature extraction steps guided by the mentioned literature

Now, considering the future direction for abnormal event detection using CNNs (Convolutional Neural Networks), Alex Net, and VGG16, we can leverage both supervised and unsupervised feature selection methods to enhance the performance of these models.

Once the models are trained and evaluated, they are deployed for real-time abnormal event detection. Deployment involves integrating the trained models into the target application environment, whether it's a surveillance system, medical diagnostic tool, or industrial monitoring system. Real-time inference is performed on incoming data streams, with detected abnormal events triggering appropriate alerts or actions.

Continuous monitoring and model maintenance are essential post-deployment activities to ensure sustained performance and adaptability to evolving abnormal event patterns. Regular retraining with updated data and periodic reassessment of model performance contribute to the long-term efficacy of the abnormal event detection system.

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| Monthly, Peer Reviewed & Referred Journal|

| Volume 7, Issue 7, July 2024 |

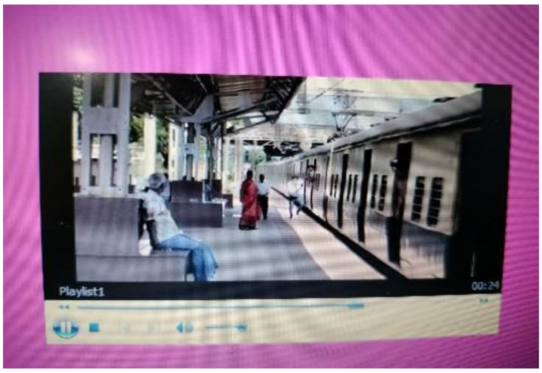
| DOI:10.15680/IJMRSET.2024.0707278 |

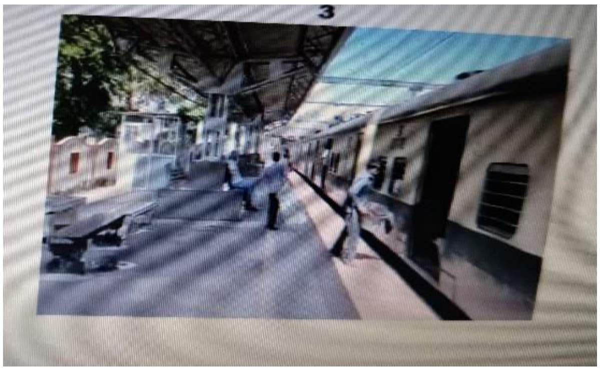
IV. EXPERIMENTAL RESULTS

Feature extraction is crucial for reducing the dimensionality of the input data while preserving relevant information. Given the nature of abnormal event detection in videos, where complex spatio-temporal patterns need to be captured, feature extraction plays a pivotal role. We can utilize a combination of traditional methods and deep learning architectures to extract discriminative features. Here are the proposed feature extraction steps guided by the mentioned literature.

Focus on identifying features that are indicative of abnormal events, such as sudden changes in motion, unexpected object interactions, or irregular object behaviour.

Leverage deep learning architectures like autoencoders or GANs to learn representations that highlight deviations from normal behaviour.





(a) **(b)**

Fig(a) describes the normal event that is occurring in Railway Station and **Fig(b)** shows the abnormal activity that is take place by the theft person.

(c)

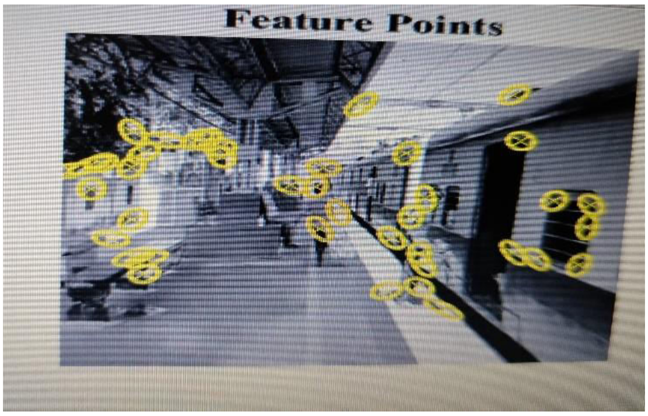
After giving the input to the application it will started to analysis the feature points of the person who is in the frame

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| Monthly, Peer Reviewed & Referred Journal|

| Volume 7, Issue 7, July 2024 |

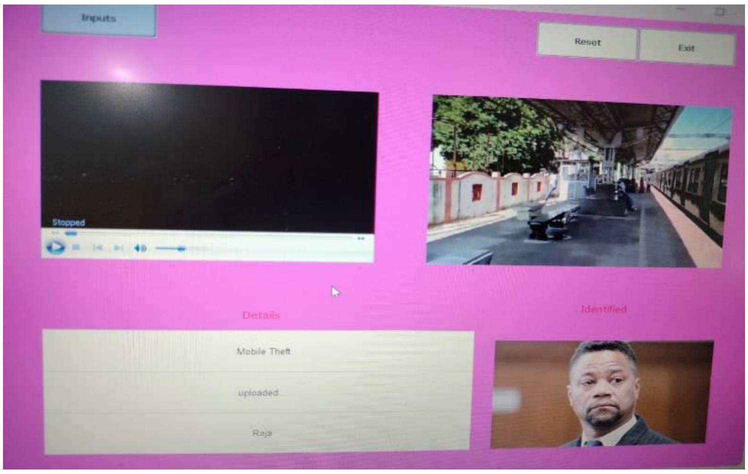
| DOI:10.15680/IJMRSET.2024.0707278 |

(d)



(e)

Fig(d) Describes the abnormal activity of the person in the railway station **fig(e)** High lighted the abnormal activities happened by the person . The abnormal activities are detected using CNN Algorithm by variation in pixel. If the feature point related to the abnormal event it will classify it further



(f)

Fig(f) identifies the details of the theft person is revealed.

V. CONCLUSION

Abnormal event detection is a prominent feature in the creation of a smart CCTV system where it is possible to automatically detect abnormalities and create the necessary alerts. Supervised learning models are commonly used in the existing systems to detect the various anomalies along with reasonable computational resources. However, since the anomalies are of various kinds, it won't be feasible to train the system to detect all types of anomalies. For this reason, supervised learning is replaced by unsupervised learning to effectively train the system. By implementing this system, we also make a system that is storage efficient by saving only the abnormal frames in high quality while the recordings would be saved in lower quality.

In the future, both supervised as well as unsupervised learning methods can be combined together to improve the system. Also anomaly identification methods could be added in the future to identify various types of anomalies as well as object detection.

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| Monthly, Peer Reviewed & Referred Journal|

| Volume 7, Issue 7, July 2024 |

| DOI:10.15680/IJMRSET.2024.0707278 |

REFERENCES

[1] J. Yu, Y. Lee, K. C. Yow, M. Jeon and W. Pedrycz, "Abnormal Event Detection and Localization via Adversarial Event Prediction," in IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 8, pp. 3572-3586, Aug. 2022, doi: 10.1109/TNNLS.2021.3053563.

[2] M. I. Georgescu, R. T. Ionescu, F. S. Khan, M. Popescu and M. Shah, "A Background-Agnostic Framework with Adversarial Training for Abnormal Event Detection in Video," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 9, pp. 4505-4523, 1 Sept. 2022, doi: 10.1109/TPAMI.2021.3074805.

[3] G. Chen et al., "Neuro AED: Towards Efficient Abnormal Event Detection in Visual Surveillance with Neuromorphic Vision Sensor," in IEEE Transactions on Information Forensics and Security, vol. 16, pp. 923-936, 2021, doi: 10.1109/TIFS.2020.3023791.

[4] Y. Yuan, Y. Feng and X. Lu, "Statistical Hypothesis Detector for Abnormal Event Detection in Crowded Scenes," in IEEE Transactions on Cybernetics, vol. 47, no. 11, pp. 3597-3608, Nov. 2017, doi: 10.1109/TCYB.2016.2572609.

[5] W. Zhang, G. Wang, M. Huang, H. Wang and S. Wen, "Generative Adversarial Networks for Abnormal Event Detection in Videos Based on Self-Attention Mechanism," in IEEE Access, vol. 9, pp. 124847-124860, 2021, doi: 10.1109/ACCESS.2021.3110798.

[6] S. CoÅŸar, G. Donatiello, V. Bogorny, C. Garate, L. O. Alvares and F. BrÃ©mond, "Toward Abnormal Trajectory and Event Detection in Video Surveillance," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 27, no. 3, pp. 683-695, March 2017, doi: 10.1109/TCSVT.2016.2589859.

[7] S. Yan, J. S. Smith, W. Lu and B. Zhang, "Abnormal Event Detection From Videos Using a Two-Stream Recurrent Variational Autoencoder," in IEEE Transactions on Cognitive and Developmental Systems, vol. 12, no. 1, pp. 30-42, March 2020, doi: 10.1109/TCDS.2018.2883368.

[8] H. Song, C. Sun, X. Wu, M. Chen and Y. Jia, "Learning Normal Patterns via Adversarial Attention-Based Autoencoder for Abnormal Event Detection in Videos," in IEEE Transactions on Multimedia, vol. 22, no. 8, pp. 2138-2148, Aug. 2020, doi: 10.1109/TMM.2019.2950530.

[9] S. Lee, H. G. Kim and Y. M. Ro, "BMAN: Bidirectional Multi-Scale Aggregation Networks for Abnormal Event Detection," in IEEE Transactions on Image Processing, vol. 29, pp. 2395-2408, 2020, doi: 10.1109/TIP.2019.2948286.

[10] Y. Liu, J. Wang, J. Li, S. Niu, L. Wu and H. Song, "Zero-Bias Deep-Learning-Enabled Quickest Abnormal Event Detection in IoT," in IEEE Internet of Things Journal, vol. 9, no. 13, pp. 11385-11395, 1 July1, 2022, doi: 10.1109/JIOT.2021.3126819.

[11] C. Sun, Y. Jia, H. Song and Y. Wu, "Adversarial 3D Convolutional Auto-Encoder for Abnormal Event Detection in Videos," in IEEE Transactions on Multimedia, vol. 23, pp. 3292-3305, 2021, doi: 10.1109/TMM.2020.3023303.

[12] P. Jiao et al., "Generative Evolutionary Anomaly Detection in Dynamic Networks," in IEEE Transactions on Knowledge and Data Engineering, vol. 35, no. 12, pp. 12234-12248, 1 Dec. 2023, doi: 10.1109/TKDE.2021.3129057.