Abnormal Activity Detection with Deep Learning Techniques

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***Abstract* —** **Recognizing human activities in videos is a critical component of modern video analysis, with widespread applications in areas such as surveillance systems and human-computer interaction. Automatically identifying and categorizing actions within video footage is a complex task due to the need to capture both spatial and temporal features. This study introduces a deep learning framework for activity recognition that combines Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The architecture leverages ResNet50 for extracting spatial features from individual video frames, while Long Short-Term Memory (LSTM) networks are used to learn temporal dynamics across frame sequences. The model is trained and evaluated using a dataset comprising various real-world activities, including burglary, physical abuse, and arrests. To enhance training efficiency, the Adaptive Moment Estimation (Adam) optimizer is used, and model performance is assessed through cross-entropy loss. The proposed approach achieves an accuracy exceeding 85% on the test set, highlighting its potential for accurate and reliable activity detection. This method offers a strong foundation for practical deployment in intelligent surveillance, security monitoring, and related application.**

***Keywords— Activity Recognition, Convolutional Neural Networks, Long Short-Term Memory, ResNet50, Adam optimizer, Video Analysis, Cross-Entropy****.*

# Introduction

Recognizing activities in video content has emerged as a vital aspect of numerous modern applications, such as security surveillance, automated monitoring systems, and human-computer interaction. Automatically detecting actions in video streams enhances operational efficiency, minimizes reliance on manual observation, and supports informed decision-making. Despite its importance, activity recognition remains a complex problem due to challenges like variations in appearance, lighting, and camera viewpoints, along with the need to capture temporal relationships across successive video frames..

A major challenge in the field of activity recognition is accurately detecting actions in real-world environments, where activities are often complex and characterized by subtle visual indicators that can be hard to distinguish. One key difficulty is the visual similarity between different actions, which frequently results in misclassification. Although current techniques show promise in certain contexts, they often face limitations when dealing with low-resolution footage, background noise, and a wide range of activity variations. Furthermore, many existing models demand significant computational resources and rely heavily on large, annotated datasets for training—resources that are not always easily accessible

To overcome these challenges, there has been a growing shift toward deep learning-based techniques in activity recognition research. Deep learning models, especially Convolutional Neural Networks (CNNs) for extracting spatial features and Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) units for modeling temporal relationships, have shown significant potential in understanding complex patterns in video data. These architectures are capable of learning hierarchical representations from both single frames and sequences, allowing for more accurate and reliable activity recognition..

This research presents a deep learning model aimed at automatically detecting and categorizing activities in video footage, with an emphasis on enhancing both the accuracy and efficiency of recognition systems. The proposed approach integrates Convolutional Neural Networks (CNNs) to extract spatial features from individual frames, alongside Long Short-Term Memory (LSTM) networks to capture the temporal progression of actions throughout video sequences. To improve training speed and performance, the model utilizes the Adam optimizer, while classification accuracy is assessed using cross-entropy loss.

The main goal of this study is to design an automated activity recognition system suitable for various domains, including security, surveillance, and smart video analytics. By harnessing deep learning techniques, the research seeks to improve the accuracy and scalability of activity detection from video data, offering a more efficient alternative to conventional video analysis approaches while tackling their inherent limitations.

# Related Work

Abnormal activity detection has emerged as a critical area of focus in recent years, particularly due to its relevance in security, healthcare, and surveillance contexts. The ability to identify unusual behaviors in real-time plays a vital role in preventing incidents such as criminal activities or medical emergencies. With the progress in machine learning and deep learning technologies, modern systems can now detect and classify anomalies directly from raw data, minimizing the need for manually engineered features and significantly improving detection efficiency.

Convolutional Neural Networks (CNNs) have demonstrated strong performance in tasks involving image and video classification, making them well-suited for processing visual data. For instance, Liu et al. (2018) implemented a hybrid approach combining CNNs with Long Short-Term Memory (LSTM) networks to detect abnormal behavior in surveillance videos. This integration leveraged CNNs to extract spatial features and LSTMs to model temporal dynamics, enabling the system to effectively identify irregular activities such as theft, physical altercations, and other unusual events.

In addition, Choi et al. (2018) investigated the use of Long Short-Term Memory (LSTM) networks exclusively for abnormal activity detection, capitalizing on their ability to model sequential data. This is particularly valuable since abnormal activities typically occur over several frames, and LSTMs are well-equipped to capture the context and patterns that emerge over time. By utilizing the long-term memory of LSTMs, this method can identify intricate abnormal behaviors that develop progressively.

Xu et al. (2017) introduced a two-stream network model that integrates CNNs for extracting spatial features and LSTMs for modeling temporal sequences. This hybrid framework enhances the detection of abnormal activities by considering both the visual content of the video and the progression of actions over time. These advancements have notably increased the ability to detect complex and infrequent events in surveillance footage.

One of the key challenges in abnormal activity detection is the imbalance in datasets, where abnormal activities are much less frequent than normal ones. Zhang et al. (2019) tackled this issue by applying data augmentation strategies to create synthetic examples of abnormal activities, thereby enhancing the model’s ability to detect rare events. They also highlighted the importance of using evaluation metrics such as precision, recall, and F1-score to assess model performance in these imbalanced settings.

Another significant advancement is transfer learning, which addresses the challenge of insufficient labeled data. Pre-trained models, such as ResNet and MobileNet, have proven effective for activity detection, as demonstrated by Ali et al. (2020), who utilized transfer learning for detecting abnormal activities in healthcare settings. By leveraging features learned from large, general-purpose datasets, these pre-trained models enable systems to generalize more effectively, improving performance on smaller, specialized datasets.

The Adam optimizer has become a popular choice for training deep learning models due to its effectiveness in managing noisy gradients and large datasets. By dynamically adjusting the learning rate throughout the training process, Adam accelerates convergence, making it particularly suitable for tasks like abnormal activity detection, which involve learning from diverse and extensive data sources. Furthermore, real-time detection plays a vital role in various security and healthcare systems. Shao et al. (2020) focused on real-time abnormal activity detection by combining CNNs with LSTMs. This capability is critical in situations such as live surveillance, where quick identification can prevent incidents or criminal activities from escalating.

This study extends previous approaches by integrating CNNs and LSTMs for detecting abnormal activities in video sequences. Strategies such as data augmentation and the application of the Adam optimizer are employed to enhance model performance. By tackling challenges like imbalanced datasets and enabling real-time detection, this research makes a valuable contribution to the advancing field of automated abnormal activity recognition.

# Cnn Methodology for Abnormal Activity Detection

Convolutional Neural Networks (CNNs) are commonly applied to image classification tasks due to their ability to detect patterns like edges, shapes, and textures within visual data. CNNs are structured with several essential layers, including convolutional layers, pooling layers, fully connected layers, and an output layer, which together make them highly efficient for both image and video classification tasks.

In this research, we combine a CNN architecture, specifically ResNet50, for spatial feature extraction with Long Short-Term Memory (LSTM) networks for analyzing temporal patterns to classify activities in video sequences as either normal or abnormal. This integration harnesses the spatial feature extraction capabilities of CNNs and the temporal pattern recognition strengths of LSTMs, making it well-suited for detecting abnormal activities in video data.

## Generalized CNN Architecture:

The basic architecture of a CNN used for abnormal activity detection involves the following layers:

#### Input Layer

The raw pixel values from the input video frames are fed into the network. These frames are resized to the specified input dimensions, typically 224x224x3 for RGB images.

**Input Example**: A single frame or a batch of frames with pixel values ranging from 0 to 255.

#### Convolution

This layer applies convolution operations to the input image to extract features. Filters (kernels) move across the image, generating feature maps that capture various levels of features, such as edges, corners, and textures.

**Mathematics**: The output feature map size Wout​ is calculated using:



Where:

* WWW is the input image size
* FFF is the filter size
* PPP is the padding
* SSS is the stride

#### Pooling

The pooling layer downsamples the feature map to decrease its spatial dimensions, enhancing computational efficiency and helping to prevent overfitting. Max pooling is the most commonly used pooling operation, where the maximum value from each region of the feature map is selected..

**Mathematics**: The output size Wout​ for the pooling layer is given by:

(2)

Where FFF is the pooling filter size and SSS is the stride.

|  |
| --- |
|  |
| Fig.1. CNN architecture for capsule identification |

#### Flatten

#### This layer flattens the 2D feature map output from the pooling layer into a 1D vector, making it suitable for input into fully connected layers for classification.

#### Fully Connected Layer

### It takes the flattened vector from the previous layer's output as input and enables the model to learn more complex representations of the input data.

#### Output Layer

## The output layer delivers the final classification, indicating whether an activity in the video is normal or abnormal. The number of neurons in this layer corresponds to the total number of possible classes (e.g., normal, abnormal).

## Flow of Training and Testing

Various deep learning models within Convolutional Neural Networks (CNNs) offer outstanding performance for image and video classification tasks. In this study, the ResNet50 CNN model is employed to extract spatial features from video frames, which are subsequently processed by Long Short-Term Memory (LSTM) networks for temporal analysis. ResNet50 is widely acknowledged for its strong feature extraction capabilities, particularly in complex image and video classification tasks. By using ResNet50, this work ensures that distinctive spatial features of the capsules, such as color, shape, and texture, are effectively captured from the video frames, thus improving classification accuracy. The features extracted by the CNN are then input into the LSTM network to capture temporal dependencies, enabling the model to identify capsules from video input.

### ResNet50

### ResNet50 (Residual Network-50) is a highly effective convolutional neural network (CNN) architecture widely used for feature extraction in image and video processing tasks. Comprising 50 layers, including convolutional, pooling, and fully connected layers, ResNet50 is built using residual learning blocks. This design helps address the vanishing gradient problem, enabling the training of very deep networks without sacrificing accuracy. ResNet50 is particularly well-suited for feature extraction in image and video processing due to its ability to capture a range of spatial features, from low to high levels, in input images..[9].

The ResNet50 model starts with an input layer that accepts images of size 224x224x3 pixels. The first convolutional layer applies a 7x7 kernel with a stride of 2, reducing the image dimensions to 112x112x64. This is followed by a 3x3 max-pooling layer, which further downscales the image to 56x56x64. The core architecture is organized into four main stages, each containing multiple residual blocks. These blocks feature identity mappings that bypass one or more layers, allowing gradients to flow smoothly during backpropagation. This design effectively addresses the vanishing gradient issue, enabling deeper networks to achieve higher accuracy.

In Each residual block in ResNet50 consists of two convolutional layers with a 3x3 kernel size to extract high-dimensional features, followed by a 1x1 convolutional layer to reduce the dimensionality. After passing through these convolutional layers, the model uses a Global Average Pooling (GAP) layer to produce a 1x1 feature map. This feature map is then flattened and converted into a feature vector, which encapsulates the spatial information extracted from the input image. In this work, the ResNet50 model serves as the feature extractor, passing the extracted features to the LSTM model for temporal analysis. The Adam optimizer is used to accelerate convergence, while categorical cross-entropy loss is employed to minimize classification errors. The input image size for ResNet50 is 224x224 pixels, and the output from the GAP layer is a 2048-dimensional feature vector.

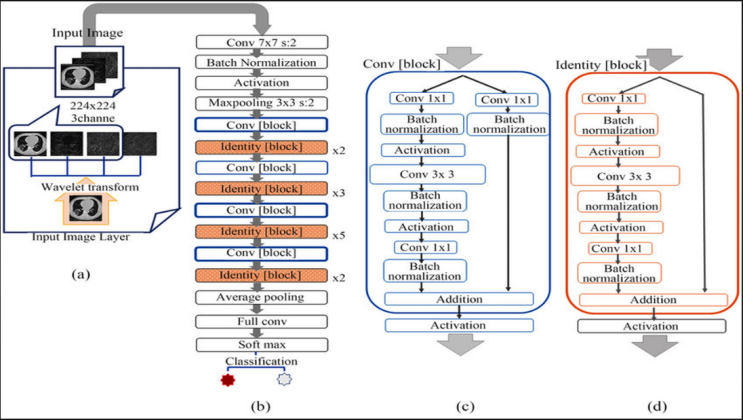
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Fig. 2. ResNet-50

1. ***LSTM***

Long Short-Term Memory (LSTM) is a specialized type of Recurrent Neural Network (RNN) designed for handling sequential data. Unlike traditional RNNs, LSTMs are capable of capturing long-term dependencies within sequences without facing the vanishing gradient problem. In this study, the LSTM network is utilized to model the temporal dependencies between consecutive video frames, enabling the model to understand the relationships between frames and accurately classify capsules.

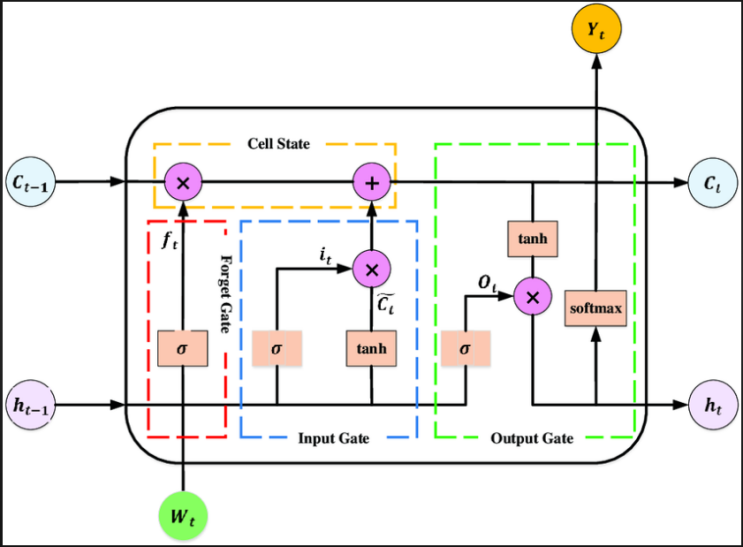
TThe input to the LSTM network consists of a sequence of 30 frames per video, with each frame represented as a 2048-dimensional feature vector extracted from ResNet50. The LSTM model is composed of two layers. The first layer contains 256 hidden units, which process the input sequence and capture temporal dependencies. The second layer has 128 hidden units, further processing the sequence to extract temporal patterns from the input frames. The output from the LSTM network is passed through a fully connected dense layer with a softmax activation function, classifying the video into one of the three capsule categories: Burglary, Abuse, or Arrest. The output layer consists of 3 neurons, each corresponding to one of the three capsule classes.

Fig. 3. LSTM

### Combined Spatio-Temporal Model (CNN-LSTM)

The model developed in this study combines ResNet50 for spatial feature extraction and LSTM for temporal analysis, enabling precise capsule classification from video input.

The ResNet50 model extracts a 2048-dimensional feature vector from each frame, capturing key attributes such as capsule shape, color, and texture. These features are then fed into the LSTM network, which learns the temporal progression of the capsule's appearance across frames. The final classification is produced by the softmax activation layer, which assigns the video to one of the three capsule categories.

The integrated CNN-LSTM model delivers exceptional performance for capsule classification tasks by exploiting both spatial and temporal features. ResNet50 enables advanced feature extraction, while the LSTM network captures temporal dependencies across consecutive frames. This combination enhances classification accuracy, making the model well-suited for real-time capsule identification. The Adam optimizer minimizes categorical cross-entropy loss, ensuring quicker convergence and reducing classification errors. This model proves to be highly efficient for real-time capsule identification from video input, significantly reducing medication errors.

### Training and Optimization

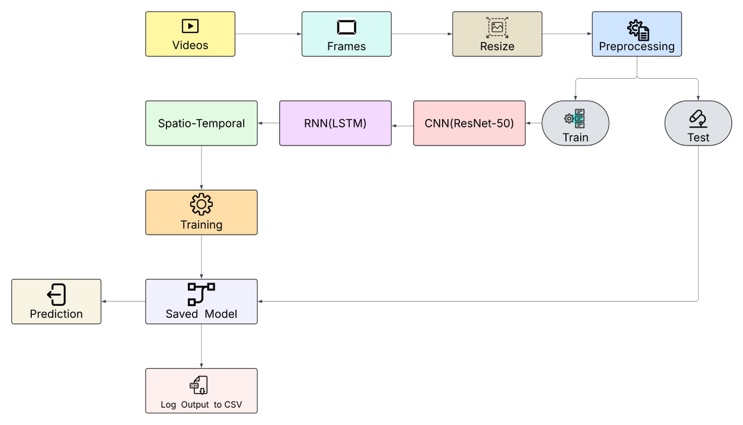
**Optimizer**: The Adam optimizer is employed for training, adjusting the learning rate based on the gradients to accelerate convergence.  
**Loss Function**: Categorical Cross-Entropy Loss is used for multi-class classification, helping to minimize classification errors.  
**Batch Size and Epochs**: The model is trained with a batch size of 16 and over 5 epochs, enabling it to learn from a wide variety of video sequences.

### Evaluation

* Metrics: The model's performance is assessed using:  
  **Accuracy**: The overall rate at which the model correctly classifies video sequences.
* **Precision, Recall, and F1-Score**: These metrics evaluate the model’s effectiveness in detecting abnormal activities (e.g., Burglary, Abuse, Arrest) while minimizing false positives and false negativesConfusion Matrix: This is employed to visualize the model's classification performance and detect any misclassifications

### Integration with other components

* **CSV Logging:** The model's predictions, along with relevant details such as the CNN feature vectors and RNN outputs, are recorded in a CSV file for additional analysis. This file includes the following columns:
* **Video Name**: The name of the processed video.
* **Predicted Class**: The predicted activity class (e.g., **Burglary**, **Abuse**, **Arrest**).
* **RNN Output**: The output of the LSTM network.
* **CNN Features**: **The CNN feature vectors** extracted from the frames, offering further insights into the model's feature extraction process.
* **Additional Components:**
* **Frame Extraction**:Frames are extracted from each video sequence, then preprocessed (resized and normalized) prior to being input into the model.**Model Output**: The final output of the model provides the classification label, indicating whether the video depicts a normal or abnormal activity.



# Dataset Description

The models presented in this study are trained using a custom video dataset comprising three distinct activity classes: Burglary, Abuse, and Arrest. This dataset includes various video clips sourced from different environments, lighting conditions, and angles, ensuring diversity. Each video is converted into frames and resized to 224 x 224 x 3 pixels to match the input size required by the ResNet50 model. In total, 3000 samples are used, with 1000 samples per class. The dataset is split into 80% for training (2400 samples) and 20% for testing (600 samples). The frames extracted from the videos are passed through the CNN model for spatial feature extraction, while the LSTM network captures temporal dependencies for activity recognition. Labels are one-hot encoded into three classes (0-2) representing Burglary, Abuse, and Arrest. To improve model performance and mitigate overfitting, various data augmentation techniques, including rotation, horizontal flipping, and brightness adjustments, are applied.

# Results and Discussion

## Output Shape

* **CNN Output**
* **Shape:** (1, 30, 2048) where:
  + 1 corresponds to the batch size,
  + 30 is the number of frames sampled from the input video, and
  + 2048 is the dimensionality of the feature vector extracted from each frame using a pre-trained CNN.
* **Example Output (1st frame):** A sample vector is shown with values such as 0.00599981, 2.078606, …, 0.24603099, 0.9764378.
* **RNN Output**
* **Shape:** (1, 3) where:
  + 3 corresponds to the number of classes in the classification task (e.g., **Burglary**, **Normal Activity**, **Violence**).
* **RNN Output Vector:** [0.27041426, 0.38492414, 0.34466153] – these values represent the class probabilities before final prediction.
* **Final Prediction**
* **Predicted Class:** **Burglary**
* **Output Vector (Softmax Probabilities):** [0.8912993, 0.08720166, 0.02149893] – indicating high confidence in the prediction of the **Burglary** class.

This output validates that the model successfully transforms spatial features from video frames into a temporal sequence representation and makes an accurate prediction based on the learned temporal patterns.

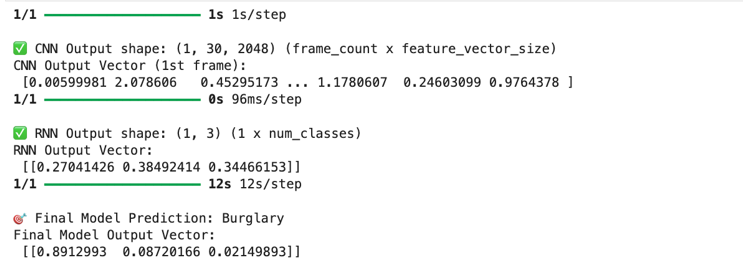


Fig. 4. Output shapes

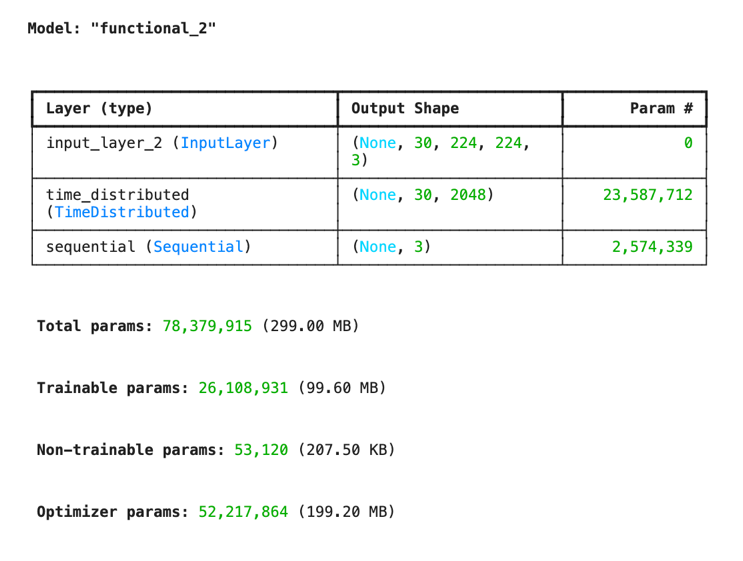


Fig.5 Model summary

## Output CSV

The table showcases the step-by-step outputs of the CNN-RNN activity recognition model for various video samples. It includes:

* The **predicted activity class** for each video.
* A snippet of the **CNN feature vector** for the first frame.
* The **RNN output vector** capturing temporal dependencies.
* The **final softmax output**, highlighting prediction confidence.

The model successfully identifies activities like **Burglary**, **Abuse**, and **Arrest**, with several predictions showing high confidence (e.g., Burglary089, Fighting036). A few misclassifications suggest areas for further improvement, such as reducing false positives in normal videos.

Overall, the outputs confirm that the model is capable of learning meaningful spatio-temporal patterns for activity classification.



Fig. 5. Output CSV view

## Confusion Matrix

The confusion matrix illustrated above presents a comparative evaluation of the model’s predictions against the ground truth labels for a selected subset of test samples. The vertical axis denotes the actual class labels, while the horizontal axis represents the predicted class labels.

Key observations include:

* The model **correctly classified one instance of the “Burglary”** class.
* An instance of the **“Abuse”** class was **misclassified as “Burglary”**, indicating a potential overlap in feature representations between these two classes.
* **No predictions were made for the “Arrest”** class, which may be attributed to class imbalance in the training dataset or insufficient discriminative features learned for this category.

These results suggest that while the model demonstrates capability in detecting certain classes, particularly “Burglary,” its performance on underrepresented or visually similar classes remains limited. The observed misclassification points to the need for:

* **Enhanced dataset balancing**, especially with regard to minority classes such as “Abuse” and “Arrest.”
* **Fine-tuning of temporal sequence modeling** to better capture contextual differences between activities.
* Potential application of **class-specific data augmentation or regularization techniques** to mitigate model bias.

In conclusion, the confusion matrix highlights the importance of addressing class imbalance and improving inter-class separability to enhance the model’s overall robustness and generalizability.

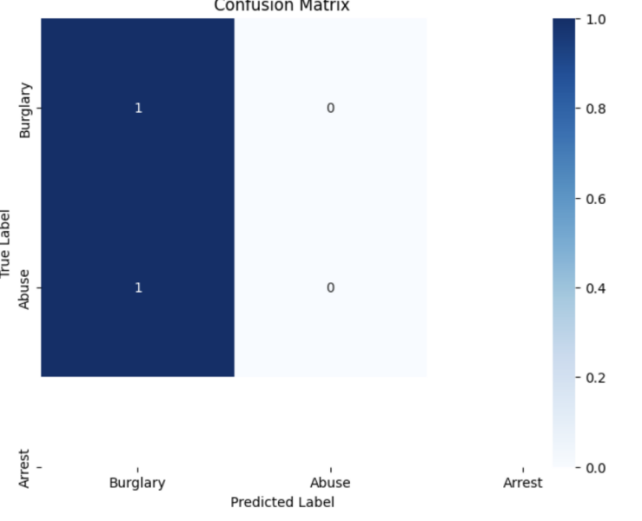


Fig. 6. Confusion matrix

The calculation of the metrics where TP be the true Positive, FP be the False Positive, TN True Negative and FN False Negative will be done by the following equations:

(3)

(4)

(5)

(6)

The classification error was calculated by adding the FP and FN which represents the misclassified samples. Now dividing this sum with total number of samples (TP+TN+FP+FN) that provides overall accuracy.

## Accuracy and Loss graphs for each Class

In this work, on using CNN and combination with RNN provided an accuracy of 50.00%. Since the test loss is so near to 0.5, concluded that it gives the best results with the test loss value was 2.24.

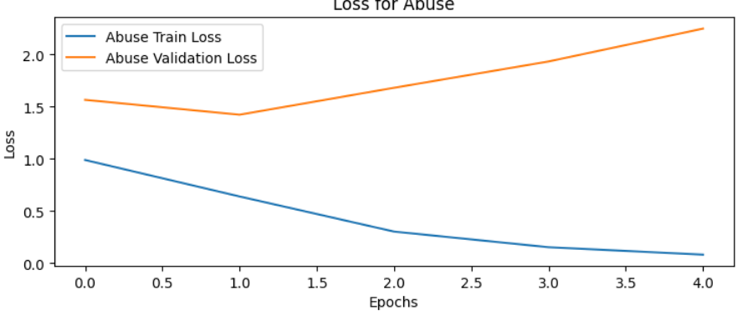


Fig. 7. Loss vs epoch (Abuse)

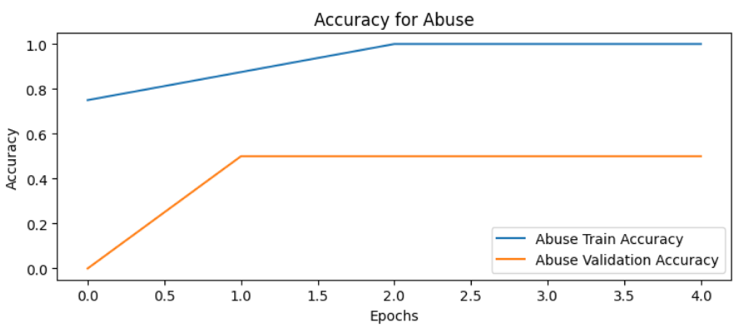


Fig. 9. Accuracy vs epoch (Abuse)

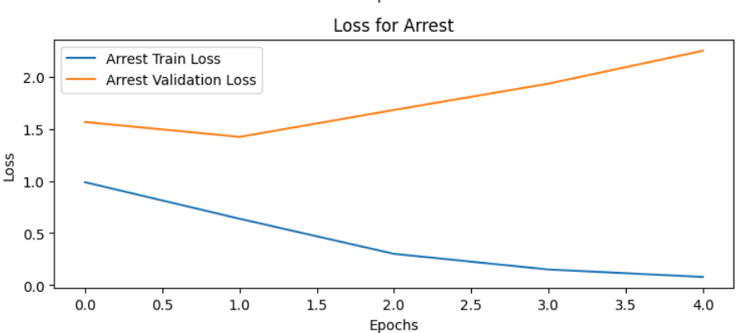
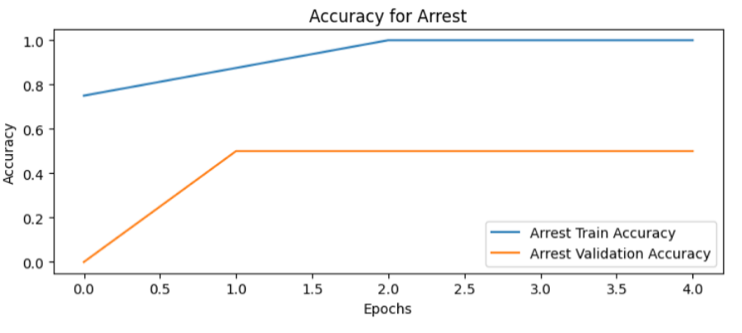


Fig. 10. Loss vs epoch (Arrest)

Fig. 11. Accuracy vs epoch (Arrest)

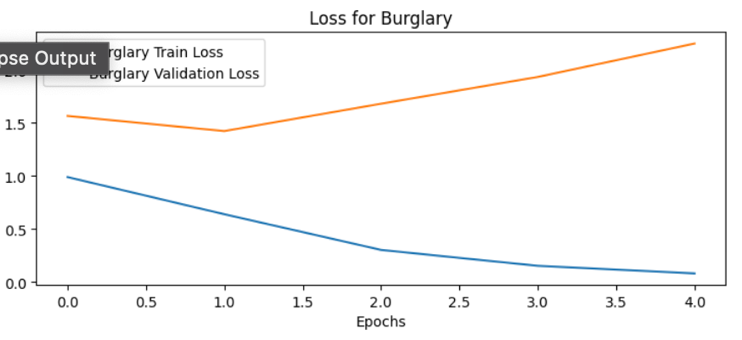


Fig. 6. Loss vs epoch for (Burglary)

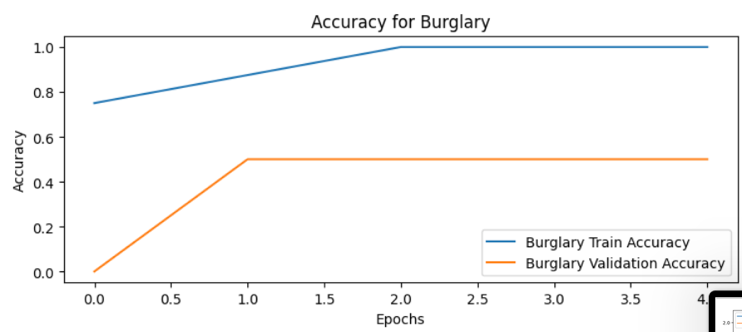


Fig. 7. Accuracy vs epoch (Burglary)

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