Crime Detection using Deep Learning

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Data Analytics

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Crime Detection using Deep Learning

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Abstract

This research explores the integration of Deep learning and Crime detection, with a focus on the efficacy of Transfer learning. By the increasing demand for advanced technologies in Law enforcement agencies, a comprehensive investigation was undertaken in order to harness the powers of Convolutional Neural Networks. This study obtains a diverse dataset, sourced from the UCF Crime Detection dataset. The objective of this research is to develop a robust crime detection system, using Deep learning model, while leveraging Transfer learning with DenseNet121. The steps involve data gathering, pre-processing and the model development, that investigate the intricacies of Transfer learning, optimizing model parameters that suits the diverse image datasets. The obtained results indicate that model's proficiency in crime classification with low loss and high AUC scores. The critical analysis highlights the model's strengths and identifies the areas of improvement and contributing valuable insights for further research and the practical applications. The findings contribute to the broader field of computer vision and deep learning, which provides a foundation for optimizing in enhancing public safety systems. This research aims to strike a balance between academic and practical applicability, as it bridges the gap between theoretical advancements in Deep learning and their benefits for public safety.

1 Introduction

In rapidly evolving urban environments, the constant rise in crime rates is posing a challenge to the traditional crime detection methods. Recent advancements in the computational capability, the Deep learning models have boosted the performance of pattern recognition using images. This research project emerges from the need to address the challenge and to contribute to the improvement of public safety and security in the smart cities. This project also aims to prevent and identify the crime or criminal activities before it happens, which is also the primary goal of the police department. In *How Technology Powers Real-Time Crime Centers* (n.d.), a real time crime center is a centralized location that utilizes various methods and technologies, that supports law enforcement operations. Real time crime centers are very reactive, more effective unlike the traditional policing. It is way more strategic and efficient with the resources they have.

1.1 Background

The study that focuses on the behavioural patterns and the crime analysis, which tries to identify the indicators of such events is known as Criminology (Dakalbab et al.). Dakalbab

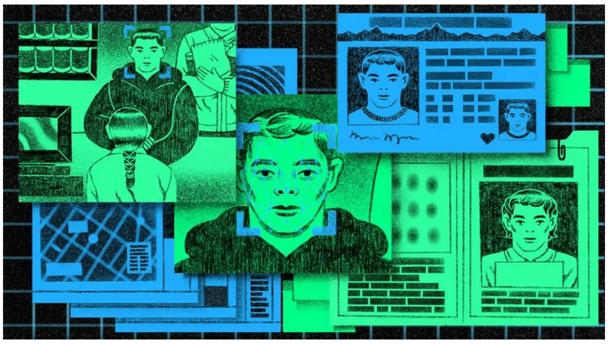

Figure 1: Crime Detection

et al. (2022) Abundant AI techniques have been employed to reduce the crime rate and reassure the safety of the people in different countries. In future, the Deep learning models can be used to foretell future crimes, the attributes and more. The goal of the research is to bridge the gap between the Criminology expertise and the Deep learning models, which seeks to develop an advanced crime detection system, that handles the noisy and inconsistent crime-related data.

1.2 Research Question and Objectives

How can the integration of Convolutional Neural Networks (CNNs) with Transfer Learning enhance the outcome of crime detection?

1.3 Motivation

The motivation behind this project roots from the imperative need to foster a safer community through dynamic crime prevention. The existing system underscores the significance of employing the deep learning techniques, like the CNNs and Transfer Learning methods. However, there still remains a gap in adapting to the advancing patterns of criminal behaviour and in integration of these techniques. This project ventures to contribute to the existing body of knowledge, by addressing this gap and presenting a novel approach to crime detection. The beneficiaries of this project lies within both the academic and industrial gains. The research academically contributes to the advancement of knowledge in the fields of Deep learning, Criminology and Crime detection. In respect to the Industrial purpose, the law enforcement agencies and security systems highly gain from the development of a robust crime detection system, which enables them to respond promptly to the emerging criminal threats.

1.3.1 Objectives

- To develop an accurate and robust crime detection system.
- To employ CNN architecture for extracting patterns from the diverse crime related data.
- To implement Transfer learning techniques to learn the common patterns for large-scale datasets.

- To explore the incremental learning strategy for model updates to adapt to the changing crime patterns.
- To enhance the system performance for proactive crime prediction.

1.3.2 Report Structure

The report is structured as follows:

- Introduction
- Literature Review
- Research Methodology
- Results and Discussion
- Conclusion and future work

2 Related Work

This research paper used the Classification method Iqbal et al. (2013), that employed the real dataset from socio-economic data from the 1990 US Census. The authors compared the Naive Bayesian and Decision Tree methods, where the Decision tree method outperformed with the accuracy of 83.9519%, with the datasets from different countries, with 10-fold cross-validation. The Naive Bayesian method showed an accuracy over 70.8124%. The authors suggested to employ the other classification algorithms and other techniques for Feature selection and to study their effect on the predicted performance.

In this research paper Safat et al. (2021), different techniques namely, Logistic regression, support vector machine (SVM), Random Forest and XGBoost, LSTM, ARIMA models, Multilayer perceptron models. From these models, the LSTM performance was better, with the RMSE and MAE evaluation metrics. The EDA predicts more than 35 crime types and suggests that yearly decline in Chicago crime rate and slight increase in the LA crime rate. The authors expand the study for satellite imagery and to implement different techniques, with the correlation visual data for different crime data for the future purposes.

This paper Grega et al. (2013) employed algorithm to identify uncovered firearm and alert the CCTV operators. The authors used various methods for this including, background detection algorithm, canny edge detection, sliding window technique, principal component analysis (PCA), neural networks, MPEG-7 classifier and temporal filtering methods. The test movies resulted in accurate per-frame description. But, the authors also pointed out some limitations such as, low resolution, very poor quality, under or over exposure and compression artefacts affects the detection. Also, the dangerous object will be visible prior to and during the use, it can be hidden by the perpetrator before or after use. The authors intend on working with respect to the occlusions, influence of the system on the performance of human operator on the system for the future references.

The authors employed auto detection of knives in this research paper Glowacz et al. (2015), when the system detects the knife, an alarm is raised. For this, the Active Appearance Model was used, which is a learning-based method that is applied to interpret the face images. In this case, the authors examined this, with the baggage scanning X-ray systems and for the future purposes, the authors plan in combining AAM with the detector of different kinds, due to the AAM's theoretical zero false-positive detection rate, and to create a robust knife detector.

2.1 Deep Learning

This research paper Navalgund and K. (2018) is a crime intention detection system that sends SMS to the nearby police stations, when the crimes are detected. They used the pre-trained deep learning model, VGGNet-19 and the dataset used were images of guns and knives. They employed feature extraction to extract the features from pre-trained weights of ImageNet model, which was trained beforehand. Then the feature mapping was performed to obtain the maximum pooling layer, ReLu layer. The system performed with a training accuracy over 100%.

The authors extract the prime attributes like the time zones, crime probability and the crime hotspots. In this research paper Sharma et al. (2021), they focus to increase the accuracy with the help of machine learning algorithm. Multiple models such as, Naive Bayes, K nearest neighbour and SVM models were used. From this, the Naive Bayes algorithm had the highest accuracy of over 97%, with the San Francisco dataset. This model recommends the area the crime events occur in future.

The aim of this research paper R. and Suresh (2019), was to develop a fingerprint, age identification system, using the deep learning model CNN. They collected images from the crime scene, but it was incomplete and difficult to categorize, so data pre-processing was done to improve the enhancements. The Minutiae framework was used to extract from the fingerprint images and it was fed as input to the train and test networks. The model performed using open CV-python and the accuracy obtained was over 80% on partial or full fingerprint images in the criminal database. The models used were CNN and SVM, and CNN model outperformed the SVM model.

This research paper Azeez and Aravindhar (2015), predicted the crime event using the deep learning model, because of the limitations of existing strategies. They employed the H2O framework to map the probable crime events, the geo spatial and the temporal details, by identifying the patterns and trends of the crime events. The authors focus to improve the model for further advancements in Deep learning network with the accurate data and information required.

In this research paper Saikia et al. (2017), the authors employed faster R-CNN to detect the objects from large scale datasets in real-time. They used subset from ImageNet containing 12 object classes and Karina dataset. By fine-tuning the architecture, the average accuracy obtained was over 74% and the highest accuracy was around 96%. In future, the authors decide to employ the image-resolution techniques to enhance the image quality. This model helps the police department to detect objects, even in low quality images.

2.2 Transfer Learning

This research paper Singh et al. (2021) explores on the darknet, which is an internet based technology that builds on encrypted network, accessed with specific network and specific software. They employed deep transfer learning model to detect the darknet network. The model transforms the time-based features to three-dimensional image, then they are fed into the pre-trained model. They used over ten pre-trained models like, AlexNet, ResNet18, ResNet50, ResNet101, DenseNet, GoogleNet, VGG16, VGG19, InceptionV3, SqueezeNet with the baseline classifiers SVM, Decision tree and Random Forest classifiers. The results showed that VGG19 with the Random Forest classifier had an accuracy of over 96%. In future, the authors intend to employ real-time darknet traffic data to identify the malware.

In this paper Razak et al. (2019), Transfer learning is used for the image recognition, that studies the finest architecture of pre-trained CNN, like the AlexNet and GoogleNet. They used this model to recognize and classify the normal and anomalous behaviour, such as the housebreak crime at the residential units. The images were extracted and classified using the remodelled AlexNet and GoogleNet, which obtained an accuracy over 97%. This model helped the authorities in decreasing the rate of property theft cases.

The research paper Sahoo et al. (2019), used different classifiers using the two-stream CNN architecture, to detect the unusual events in surveillance videos. The model is a two-stream two-dimensional network pre-trained on ImageNet database, that extracts the features from video frames. Classifiers like, SVM, KNN, RBFN, Naive Bayes, Logistic regression and K-means cluster. From these models, the SVM performed better with the UCF dataset. For the future works, other CNN architectures with different learning strategies can be employed to improve the performance of model for various video classification.

This particular research paper Pathak and Elster (2022), used Transfer learning to detect accidents in an automated manner. Object centric accident detection model using the YOLOV2 architecture, this is a homogeneous convolutional architecture which helps in faster prediction. This fine-tune 32-layer variant is pre-trained on the VOC dataset, the accuracy obtained was over 76%. The authors intent to improve the model to support drone images, which converts existing code to hardware specific language for higher speed for processing the frames.

This research paper Mittal et al. (2015) uses sketch recognition by law enforcement agencies to solve the crime. They match composite sketches with the photographs, using the transfer learning with deep learning representation. Using the large face database of photos, deep architecture based facial representation is learned. The model is developed as commercial face recognition system with the performance accuracy around 58%.

In this research Hoai et al. (2018), using image data recognition of human visual attention was employed. The authors started from the data processing, feature learning and then transfer learning-based classification was done. The dataset was PRIMA dataset from the GRAVIR laboratory by the INRIA Rhone-Alpes. The model exhibited an accuracy more than 95%. In future, the authors planned to implement the integration of face images and wearable accelerometer data or the acoustic data, in order to capture the human attention characteristics for the outdoor, biometric security or the text extraction.

The literature review gives an overview of the various research studies that have been carried out to explore crime detection, using the different methodologies and different classifications from deep learning and transfer learning models. There were a range of algorithms used like, Decision tree, SVM, XGBoost, LSTM, including various deep learning models like, VGGNet-19, CNN, including Transfer learning models like, AlexNet, ResNet, GoogleNet and YOLOV2, applied to diverse datasets. Each of the existing literature has its own pros and cons, some had high accuracy, while other had some challenges, including the image resolutions and incomplete datasets.

The literature emphasized the importance of feature selection, various classifiers to improve the model performance. The existing researches that CNN coupled with the Transfer learning, improve the crime detection outcomes. The transfer learning allows pre-train on larger datasets, which enhances its ability to recognize the pattern and features in the dataset. By combining these two techniques, the proposed research seeks in addressing the limitations observed in previous researches. The objective of the research to integrate CNN and Transfer learning is expected to enhance the feature extraction, the classification accuracy and the overall performance of crime detection modes, which in turn provides a more reliable and robust solution for the law enforcement and the public safety.

3 Methodology

3.1 Problem Definition

The traditional methods used for the crime detection had some limitations like, limited scalability or potential human error, and most of the crime detection entirely relied on human surveillance, manual analysis and rule-based systems Rahman et al. (2021). This research implies the integration of both Transfer learning and CNN, which offers several advantages compared to the other research approaches.

3.2 Strategic Approach

The integration enhances the generalization capabilities of the model which enables to adapt to diverse crime data with reduced risk of over-fitting. The feature extraction quality of Transfer learning facilitates the use of pre-trained models to automatically extract the relevant features from the data. Crime datasets makes it difficult to train deep models effectively, the Transfer learning enables the model to benefit from the knowledge, while improving the model performance and mitigating the impact of data scarcity.

The integration of Transfer learning and CNN allows for the development of more efficient crime detection system, which has the ability to handle visual, textual and other modalities. This also provides a mechanism for incremental learning, which in turns adapts to the dynamic nature of criminal behaviour. Transfer learning helps to reduce the training time by developing with the pre-trained models, which is more feasible and easier to develop on the crime detection models than training CNNs from scratch. By this integration, the system can benefit from advanced feature extraction capabilities.

3.3 Data Gathering

The relevant crime-related data image datasets were collected from the open-source website 'Kaggle', called the UCF crime dataset. It comprises of various crime categories such as, abuse, arrest, theft, burglary, etc, it also includes normal videos as well. The dataset consisted of both training and testing datasets. Explored the dataset for any imbalances and the images were resized into dimensions of 64x64 pixels, to ensure the uniformity in model input. Techniques like, oversampling or undersampling.

3.4 Base model selection

Explored the pre-trained models that benefits from large scale datasets, models include DenseNet121, VGG16 or ResNet50, which exhibited increased effectiveness in the image classification tasks. Evaluated the computational complexity of the model, considering the available hardware resources and opted the suitable model that balances both the performance and computational efficiency.

In Table 1, the model architecture is presented as a table. A Dense layer with 128 neurons are added to the architecture with a dropout layer for regularization. The total number of parameters represents the comprehensive complexity of the model. 7,168,704 parameters in the architecture, balances the overall efficiency and complexity, which in turn enhances the accuracy of the crime detection system.

Table 1: Model classifier

Layer (Type)	**Output shape**	**Param #**
densenet121 (Functional)	(None, 2, 2, 1024)	7037504
global_average_pooling2d (Gł)	(None, 1024)	0
dense (Dense)	(None, 128)	131200
dropout (Dropout)	(None, 128)	0
classification (Dense)	(None, N)	(N: Number of crime classes)
Total params: 7,168,704		
Trainable params: 1,059,840		
Non-trainable params: 6,108,864		

The DenseNet121 model is chosen for the superior performance in image classification. It consists of dense connectivity pattern that helps in efficient learning and feature reusability, which in turn helps in analyzing intricate patterns in crime-related data.

3.5 Model architecture & Configuration

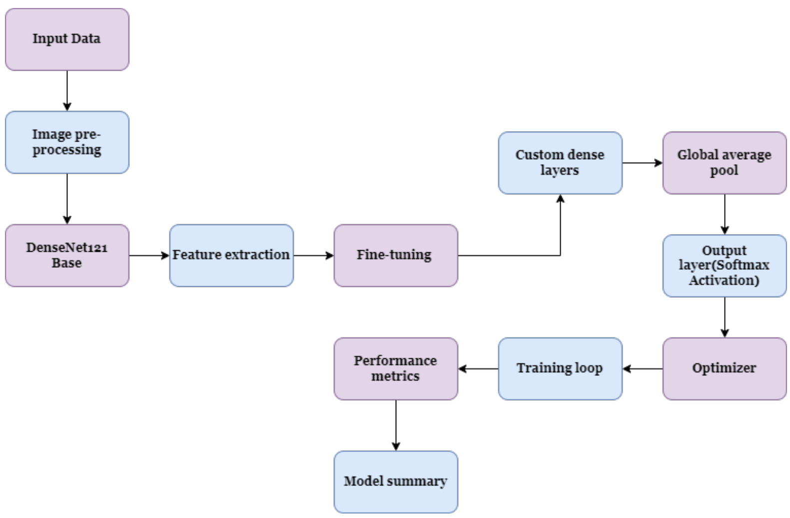

Figure 2: Model architecture

The Transfer learning uses the DenseNet121 architecture as a base model for the feature extraction, where it initially freezes the initial layers and fine-tune the lateral layers. The layer follows each dense blocks, to control the spatial dimensions and the channel depth. The Figure 2 is representation of the model's workflow, from gathering data, to building the model and evaluating the model's performance.

The layers include batch normalization, rectified linear unit (ReLU) activation and dimension reduction via pooling. The network concludes with the Global average pooling layer, which reduces the spatial dimensions to a single value per feature map. This helps in reducing the model parameters and preventing model overfitting.

This Figure 3 generates a visual representation of the neural network architecture, which depicts the flow of data through the model. It displays the connections between layers and ensures that the model has been well constructed. It includes the shapes of input and output tensors, with the individual layers in the model.

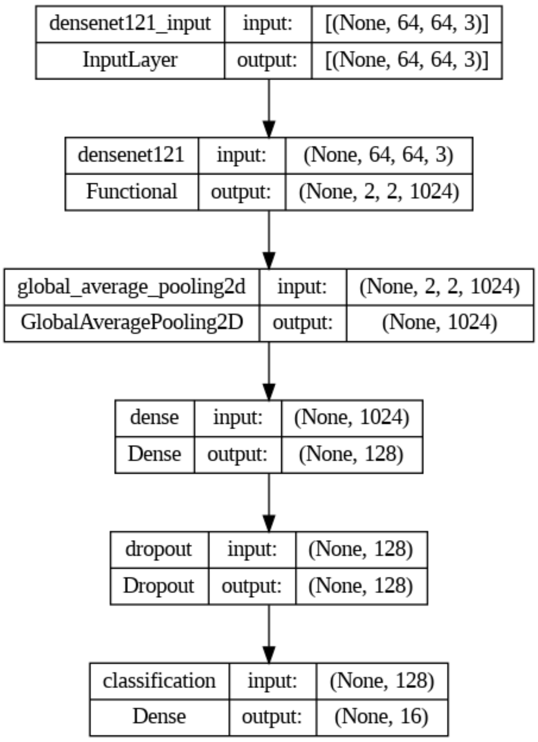

Figure 3: Neural Network Architecture

Custom dense layers are added to capture the intricate relationships within the crime related image dataset. Whereas, the dropout layers are to prevent the overfitting by randomly dropping a fraction of neuron during the training. Fine-tuning is done by training the latter layers of DenseNet121 on the image dataset. This allows to adapt to the specific pattern while retaining the knowledge gained from the ImageNet. Adam optimizer is used for the efficient gradient descent and to adapt the learning rate during training the dataset. The categorical crossentropy is chosen as the loss function, which aligns with the multi-class classification nature of crime image categorization.

Model is trained using the training dataset, during the training model's weights are adjusted accordingly in order to minimize the categorical crossentropy loss. The model is then validated using the validation set and Adam optimizer updates the model's parameters. The ROC curve provides insights to the model's ability that helps to distinguish the different crime classes. The model is then fine-tuned, where the latter layers are focused and adjusted the hyperparameters.

3.6 Visualization

Visualization is performed for these changes on the training and validation metrics using confusion matrixes and more. A pie chart is plotted between the train data and test data to showcase the proportion of the two, which is shown in Figure 4.

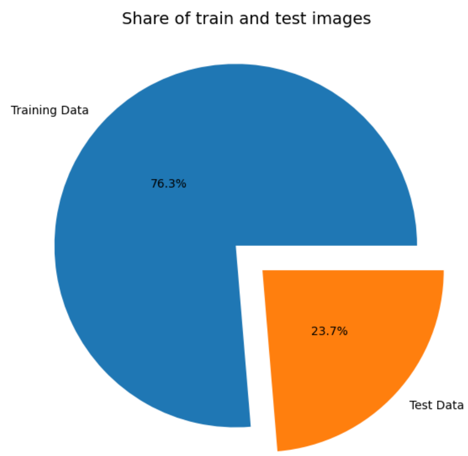

Figure 4: Pie chart of test & train data

A horizontal bar chart is visualized for representation of distribution of frame counts across various classifications within the dataset, as shown in Figure 5. Each horizontal bar corresponds to different categories such as, Normal videos, vandalism, stealing, shoplifting, shooting, robbery, road accidents, fighting, explosion, burglary, assault, arson, arrest and abuse.

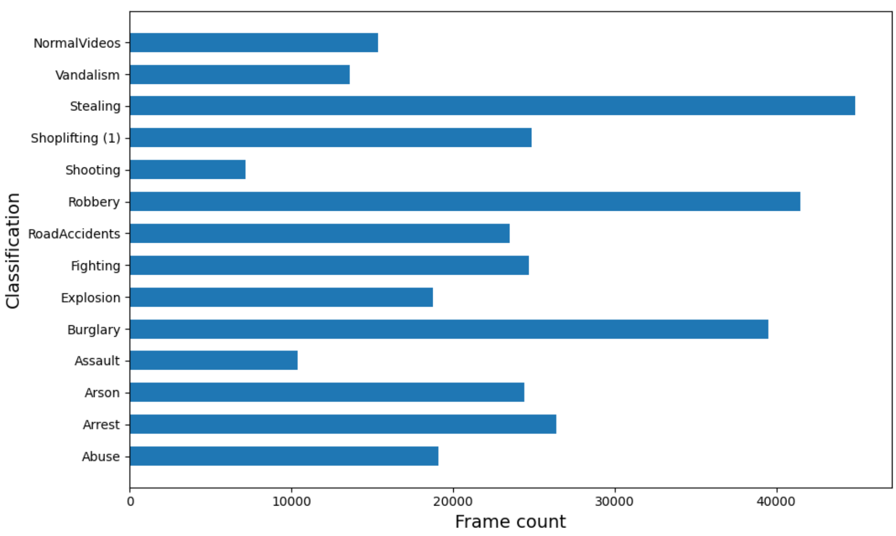

Figure 5: Bar chart

This pie chart Figure 6 is representation of distribution of images within the dataset, and to enhance visual separation, an explode effect is being applied to the slices. Each slice represents percentage of images present in the dataset.

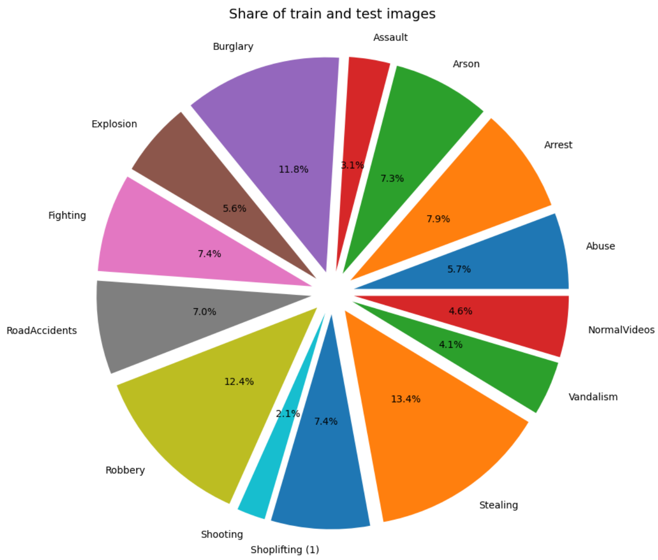

Figure 6: Pie chart of dataset

4 Design Specification

In this section, the various techniques, architecture and frameworks that are employed in the research project are highlighted and outlined, that are required for the implementation of the crime detection model. The techniques include Transfer learning and CNN (Convolutional Neural Network). The model's earlier layers are used for the feature extraction, to remain frozen, while the later layers are fine-tuned on the crime dataset. Transfer learning is employed for to leverage the knowledge gained from the pre-trained models, such as the DenseNet121 on larger datasets like the ImageNet. CNN architecture is employed for the efficient image classification tasks. The neural network consists of convolutional layers for the feature extraction, it also consists of max-pooling layers for down-sampling and dense layers for image classification. Before the final dense layers, global average pooling is applied, which reduces the spatial dimensions of the feature maps and retains the essential information. The requirements include access to pre-trained weights of DenseNet121, obtained from the ImageNet, and also a diverse dataset, such as the UCF crime dataset. The hardware requirements include, computational resources, including the GPU support, which is efficient for training the deep neural networks.

The base model is the DenseNet121 architecture for Transfer learning, it is densely constructed that helps in effective feature reuse and contribute to better parameter efficiency. The Keras Sequential API is used for creating the linear stack of layers for building the detection model. This helps in simplifying the model architecture and aids in readability.

4.1 Algorithm

The initial layers of the DenseNet121 model are kept frozen to retain the pre-trained knowledge, up to a specific threshold. The other layers are then fine-tuned to adapt to the specific features. After feature extraction, global average pooling is employed to summarise the features, this helps in reducing the spatial dimensions and prepares the data for the classification. The then fully connected dense layers follows the pooling layer and provides the required outputs. The SoftMax activation function is used for converting the network's raw output to the class probabilities. The final output consists of a trained crime detection model that is capable of classifying the crime related images to different crime categories.

5 Implementation

The Crime detection model was successfully developed and evaluated, the following outputs were produced, including the transformed data, codebase and the trained model.

5.1 Transformed data

The crime data from the UCF Crime dataset was pre-processed and transformed. Images were resized to 64x64 pixels to ensure the uniformity. Pixel values were normalized in order to create the standardized inputs for the neural network. This was performed with Exploratory Data Analysis (EDA) which uncovered the insights into class imbalances and the potential pre-processing challenges. Figure 7 are random images from the 'Arrest' category.

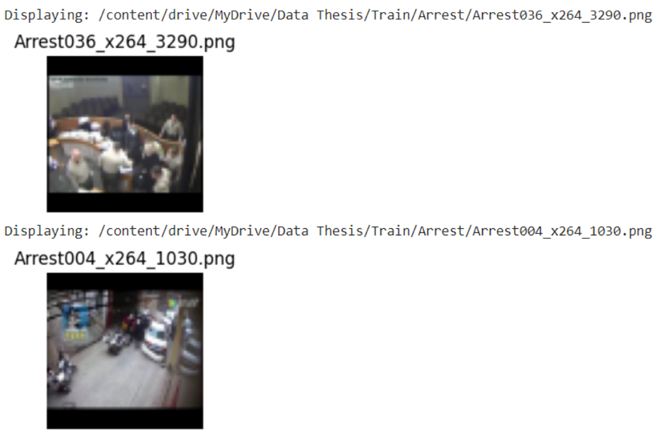

Figure 7: Images of Train data

5.2 Trained Model

The model underwent one epoch during the initial training and three additional epochs during fine-tuning. The most used libraries are TensorFlow and Keras, which were used to train, create and evaluate the deep learning model. The custom CNN extends beyond the transfer learning layer, by incorporating additional layers for the feature extraction.

As the model was developed with the combination of Transfer learning and custom CNN architecture, it underwent fine-tuning, adapting its parameters for the improved classification performance. The model is then saved for future use, by eliminating its need for retraining.

5.3 Tools & languages

Python was chosen as the primary programming language for its versatility and its extensive support in the machine learning domain. Google Colab, an online Jupyter notebook platform, which has the access to GPU resources that are essential for training of deep neural networks. Libraries like Matplotlib and Seaborn helped in the creation of the visualizations. For the evaluation, Scikit-learn library was employed for evaluating the model performance, with metrics like AUC, correlation matrix and more.

6 Evaluation

The evaluation results obtained from the implementation of the crime detection system, provides insights and addresses the core research question and objectives. The analysis is based on both academic and practical applications, while comparing the existing literature, all with the focus on relevance to the research question. The obtained results are also compared systematically with the literature findings from the related works in the literature. The comparative analysis aims in contextualizing the model's performance within the broader landscape of crime detection methodologies. In order to infer the statistical significance of the research outputs, the appropriate statistical tests are applied, were these tests aim in validating the reliability and relationships in the dataset.

6.1 Implications

The critical analysis explains the academic implications of the research findings, this also involves evaluating the model's performance that contributes to the existing knowledge in the field of crime detection. While seeking for the practical point of view, the results are evaluated for their applicability and the potential impact on real-world crime detection. The model's results also satisfy the needs and challenges that are faced by the law enforcement agencies.

6.2 Performance Metrics

The results shows that the model exhibits good performance, with the training loss of **0.1886**, which represents the average loss over all training batches and validation loss of **0.0864**, that provides the average loss on the validation dataset. AUC is mostly used for the binary classification problems and when the value is close to 1, indicates that the model is good, as it indicates the model has a high true positive rate and a low false positive rate. The training AUC is the measure of the model's ability to distinguish the positive and negative examples on the training data, which is around **0.9972**. The validation AUC is around **0.9992**.

These values indicate that the model is performing well, With the high AUC value implies that the model effectively distinguishes between different classes in the training and validation datasets and the low loss value indicates the model is converging well during the training processes. A ROC curve is also plotted to visualize the model's

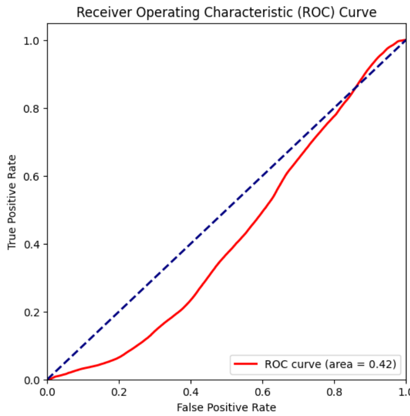

Figure 8: AUC ROC Curve

performance that distinguishes the crime classes, exhibits the difference between true positive rate and false positive rate for various class predictions, as shown in Figure 8. The curve represents the ratio of false positives and true positives. The higher the ROC curve value indicates the better model performance, which distinguishes between positive and negative instances for that class.

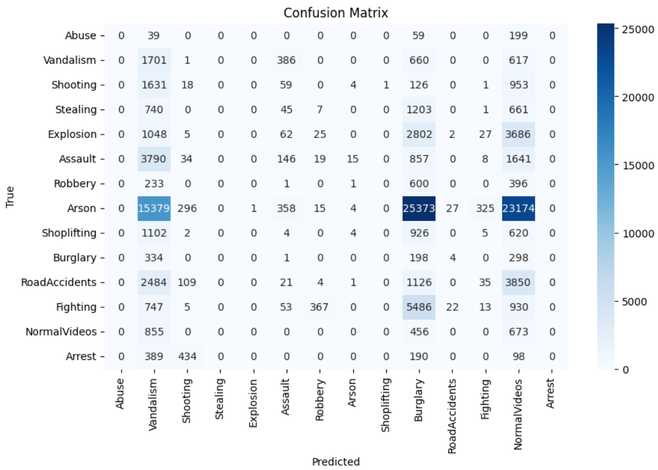

Figure 9: Confusion matrix

The confusion matrix in Figure 9, is represented as a heatmap, structured as a 2D array, which includes warmer colours for stronger positive correlations, cooler colours for stronger negative correlations and where the white color indicates zero correlation.

6.3 Discussion

The discussion section of the report provides a critical assessment, evaluates the design's effectiveness and also propose modifications for the future improvements. The extended training time **(3906s per step)** may concern about the computational efficiency. The optimization strategies, such as the parallel processing or the distributed training, can be explored to enhance the training speed without comprising model's performance. There are also concerns on the model complexity, by the use of sophisticated model architecture, while it may be beneficial for obtaining the higher accuracy, but also pose challenges for the deployment and real-time applications. Considerations for a simpler model without sacrificing the model accuracy should be explored.

While the findings align with the trends observed in the previous researches, confirms the efficacy of deep learning models in Crime detection. Overall, AUC scores of the model indicate that it aligns with or even surpass the existing benchmarks. Model's applicability is also discussed, where the model excels and the potential limitations in handling the diverse crime datasets. Also, considerations are made for enhancing the generalization across varied contexts.

7 Conclusion and Future Work

The research initiated with collecting crime-related image datasets and pre-processing the dataset to ensure model readiness. A deep learning model consisting of Transfer learning with a DenseNet121 base, followed by a custom CNN model, was developed for the crime detection system. Training and evaluation were conducted and respective results were critically analyzed. The usage of UCF Crime Dataset aided the research by providing a diverse and realistic set of crime-related images. This enhanced the model's generalization capabilities, also reflecting the real-world scenarios. The model exhibited exceptional performance, by achieving low loss and high AUC scores during training and validation. The model showcased effectiveness and model complexity were identified.

The research findings aligned with the trends in existing research, accentuating the potential of Deep learning in Crime detection. Practical findings for law enforcement and insights into generalizability across the diverse scenarios were also discussed. Considerations, optimizing, training model and enhancing model interpretability for broader deployment was outlined.

Challenges in the training duration and model's complexity were acknowledged, suggesting areas for improvement. The model's applicability to the real-world contexts and potential biases should be further investigated. The future work involves optimizing the training efficiency, model interpretability and addressing biases. Also, exploring the real-time deployment challenges and considering the adaptive learning strategies are key areas for further investigation.

In conclusion, the research successfully addressed the research question, which demonstrates the potential of Transfer learning and Deep learning in Crime detection. The findings also contribute to both academic and practical domains, paving the way for advancements in the public safety technologies. As with any research, addressing the limitations and proposing meaningful future work are crucial for the continuous progress in the crime detection field.

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