1. **Intelligent video surveillance: a review" by G. Sreenu and M. A. Saleem Durai, published in 2019.**

This paper provides a comprehensive review of intelligent video surveillance techniques, with a particular focus on deep learning methods for crowd analysis. It begins with a general overview of video surveillance and then narrows its focus to the more challenging area of crowd analysis and violence detection. The authors highlight that manual surveillance is tedious and time-consuming, and that intelligent systems are necessary, especially in crowded public places. The survey identifies and summarizes issues in existing methods and suggests future research directions to overcome them.

The paper categorizes and discusses different approaches to video surveillance, including those that are **not** based on deep learning, such as rule-based systems, and those that heavily utilize deep learning. Key deep learning models reviewed for surveillance analysis include CNNs, auto-encoders, and their combinations. The paper also emphasizes the importance of **real-time processing**, which remains a significant challenge. The authors conclude by noting that while existing methods are effective for individual and small group analysis, they struggle with large, dynamic crowds and the various real-world constraints like bad weather and object occlusion.

**Paper Details**

* **Title and Year:** "Intelligent video surveillance: a review" by G. Sreenu and M. A. Saleem Durai, published in 2019.
* **Datasets Used:**
  + **Image Datasets:** ImageNet2012 and PASCAL VOC.
  + **Video Datasets:** CAVIAR, BEHAVE, YTO, I-LIDS sterile zone, PETS 2001, MOSIFT, STIP, MediaEval 2013, UCSD Pedestrian, UMN, Subway, U-turn, PETS2009, AGORASET, Rome Marathon, WWW Crowd, Violent-flows, CUHK, UCF50, Rodriguez's, The mall, WorldExpo's, and the Shanghai Tech dataset.
  + **Other Datasets:** Frames Labeled In Cinema (FLIC) and Leeds Sports Pose (LSP).
* **Approaches/Techniques:**
  + **Deep Learning Methods:** CNNs, auto-encoders, Long Short-Term Memory (LSTM), You Only Look Once (YOLO) network, and VGG-16 Net.
  + **Other Methods:** Rule-based systems, Threshold Models, Bayesian Networks, Bag of Actions, Markov logic networks, Gaussian Mixture Models (GMM), Hidden Markov Models (HMM), and optical flow-based methods.
  + **Frameworks:** Apache Spark framework for real-time processing.
* **Limitations of Existing Methods:**
  + **Real-world challenges:** Existing solutions do not handle all real-world constraints simultaneously.
  + **Computational overhead:** Some deep learning models, like AMDN, have high computational overhead during testing, making them unsuitable for real-time processing.
  + **Difficulty in specific tasks:** Differentiating similar actions like punching and pointing is challenging. Also, current methods are not effective in handling large, dynamic crowd scenes.
  + **Lack of automatic feature identification:** Traditional methods are not efficient in automatically selecting good features.
  + **Problematic scenarios:** Existing methods struggle with bad weather, object occlusions, object overlapping, and real-world dynamics.
* **Suggested Future Works:**
  + Developing new models or combining existing deep learning architectures to handle all real-world problems simultaneously.
  + Improving systems to handle real-time processing effectively.
  + Reducing the time taken for response generation.
  + Exploring solutions for issues such as bad weather conditions and object occlusions.
  + Creating methods that can effectively handle the analysis of crowd scenes.

1. **Analysing Crime Patterns using Machine Learning: A case study in Chicago" by Himanshi Himanshi, submitted in 2022.**

This research project aims to analyze and predict crime patterns with high accuracy using machine learning, specifically focusing on a case study in Chicago. It proposes a hybrid framework that combines deep learning and traditional machine learning methods to forecast crime rates. The study utilizes a large dataset of Chicago crime incidents from 2001 to 2021, and focuses on crime rate prediction based on time and location. The paper details the data preparation process, including handling missing values, outliers, and irrelevant columns, and the subsequent data modeling using various time series models. The performance of six different models (Simple Moving Average, Weighted Moving Average, Exponential Moving Average, Bidirectional LSTM, CNN-LSTM, and Random Forest Regression) is evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics. The research found that the Bidirectional LSTM model outperformed the other models in terms of RMSE, and that day-wise predictions showed significant improvements over weekly and monthly predictions.

The study also provides an exploratory data analysis to understand crime patterns, such as which days, months, and years have the highest crime rates, and the impact of the COVID-19 pandemic on criminal activities. The paper concludes that the proposed framework is effective for crime pattern analysis and forecasting, and suggests future work to further optimize the models and incorporate additional spatial and temporal factors to improve prediction accuracy.

**Paper Details**

* **Title and Year:** "Analysing Crime Patterns using Machine Learning: A case study in Chicago" by Himanshi Himanshi, submitted in 2022.
* **Dataset Used:** Chicago city crime dataset from 2001 to December 2021. The initial dataset had 9,159,279 rows, which was reduced to 6,259,111 after data cleaning and transformation. The dataset contains 24 columns after processing.
* **Approaches/Techniques:**
  + **Data Pre-processing:** Data merging using pandas.concat() , null value removal using dropna() , and duplicate row removal using drop\_duplicates().
  + **Feature Engineering:** Feature selection was performed by dropping primary crime types with low frequency and keeping the top 24 crime types. Outliers were also removed from location descriptions and community areas. Numerical features were normalized using MinMaxScaler.
  + **Models:** The research utilized a hybrid framework combining deep learning and traditional machine learning.
    - **Deep Learning:**
      * Moving Average Models (Simple, Weighted, and Exponential).
      * LSTM Models (1-layer, Bidirectional, and CNN-LSTM).
    - **Traditional Machine Learning:**
      * Random Forest Regression.
      * ARIMA.
  + **Evaluation:** Model performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).
* **Limitations:**
  + The study did not consider spatial-temporal factors that might affect the crime rate, such as weather, road conditions, and proximity to police stations.
  + The models were unable to accurately predict the year-end dip in crime numbers on a week-by-week basis.
  + The Random Forest model struggled to predict sudden spikes and drops in crime during volatile periods like 2019-2021.
  + A previous study mentioned a weakness in their model where it "cannot perform well for data more than three years".
* **Suggested Future Works:**
  + Optimizing the models and setting up a statistical methodology to select the best final model based on metrics like RMSE, MAE, and size.
  + Expanding the study to include different crime datasets and apply different learning techniques.
  + Incorporating visual data and satellite imagery to provide more effective anticipation of criminal events.
  + Developing a crime detection model that considers spatial and temporal factors.

1. **Chicago Crime Analysis using R Programming", published in 2019.**

This paper presents an analysis of crime data in Chicago using the **R programming language** and a **K-Nearest Neighbor (KNN) classification algorithm**. The main goal of the research is to predict the likelihood of an arrest for a given crime incident. The study uses the "Crimes (2001-Present)" dataset from data.cityofchicago.org. The authors performed various data cleaning and preprocessing steps, including reducing the dataset to the years 2015-2018, handling missing values, and converting different crime types into broader categories.

The paper's findings are based on an exploratory data analysis, which shows a steady decline in crime rates in Chicago over the years. The analysis also identifies patterns such as the most common crime types and locations, and how crime frequency varies by month and day of the week. For the prediction model, the dataset was split 80:20 for training and testing. The KNN model achieved an accuracy of 83.2% when using a **k-value of 9**.

**Paper Details**

* **Title and Year:** "Chicago Crime Analysis using R Programming", published in 2019.
* **Dataset Used:** "Crimes (2001-Present)" from data.cityofchicago.org, but the analysis focuses on data from 2015-2018.
* **Approaches/Techniques:**
  + **Data Analysis and Visualization:** Exploratory Data Analysis (EDA) was performed using the highcharter and ggplot libraries in R.
  + **Data Preprocessing:** The dataset was reduced to a specific time period (2015-2018), variables were converted to categorical types, and missing values, whitespaces, and duplicate observations were removed. Different types of crimes were also grouped into broader categories.
  + **Prediction Model:** K-Nearest Neighbor (KNN) classification was used to predict the likelihood of an arrest.
* **Limitations:**
  + The paper does not mention any limitations of the approach or model used. It focuses on the results and effectiveness of the KNN algorithm for the specific task of predicting arrests.
  + The study is based on a reduced dataset (2015-2018), which may limit the generalizability of the findings.
* **Suggested Future Works:**
  + The paper mentions that "Discussions on future investigation can also be found" but does not explicitly list any suggested future work in the text. However, the use of the model to design "precaution methods in the future" is mentioned in the conclusion.

1. **Crime Rate Inference with Big Data" by Hongjian Wang, Daniel Kifer, Corina Graif, and Zhenhui Lit, published in 2016**

This paper explores the use of new urban data sources—Points-of-Interest (POI) and taxi flow data—to improve the accuracy of crime rate inference at the neighborhood level in Chicago. The authors argue that traditional methods relying on demographics and geographical proximity are insufficient because they fail to capture the dynamic nature of urban environments. The research proposes a new approach that incorporates POI data to reflect a neighborhood's functionality and taxi flow data as "hyperlinks" to model social interactions between non-adjacent regions.

The study uses a dataset of over 5.8 million crime incidents from 2001 to 2015, along with POI data from Foursquare and taxi trip records from late 2013. The performance of linear regression and negative binomial regression models is systematically compared under various feature combinations. The results show that the negative binomial regression model significantly outperforms linear regression for this task. The study also demonstrates that adding POI and taxi flow features considerably improves crime rate inference, reducing the prediction error by up to 17.6% in the best-case scenario.

**Paper Details**

* **Title and Year:** "Crime Rate Inference with Big Data" by Hongjian Wang, Daniel Kifer, Corina Graif, and Zhenhui Lit, published in 2016.
* **Dataset Used:**
  + **Crime Data:** 5,856,414 recorded crime incidents in Chicago from 2001 to 2015, obtained from the City of Chicago data portal.
  + **POI Data:** 112,000 POIs from Foursquare.
  + **Taxi Flow Data:** 1,048,576 taxi trips in Chicago from October to December 2013, acquired through the Illinois Freedom of Information Act.
  + **Demographic Data:** 2000 U.S. Census Bureau's Decennial Census data.
  + **Geographical Data:** Boundary shape files of Chicago.
* **Approaches/Techniques:**
  + **Models:** The study compares linear regression and negative binomial regression models for crime rate inference.
  + **Feature Engineering:** The research uses a combination of four feature types:
    - **Nodal Features:** Demographics (e.g., population, poverty, ethnic diversity) and Point-of-Interest (POI) distribution.
    - **Edge Features:** Geographical influence and taxi flow (hyperlinks).
  + **Evaluation:** Performance is measured using Mean Absolute Error (MAE) and Mean Relative Error (MRE) with a leave-one-out evaluation approach.
  + **Feature Construction:** The paper discusses effective methods for constructing features, such as using raw POI counts instead of percentages and normalizing taxi flow by destination.
  + **Feature Importance Analysis:** Permutation tests and coefficient analysis are used to determine the significance of each feature.
* **Limitations:**
  + Traditional demographic data is static, as it is collected only every 10 years, and only provides partial information about a neighborhood.
  + Using only demographic data results in a relative error of at least 30%.
  + Adding geographical influence to demographics provides minimal improvement (at most 0.4% relative improvement).
  + The taxi flow feature can result in a relatively large estimation error in downtown areas due to skewed data distribution, as about 61% of trips have a destination there.
  + The study does not consider the temporal dimension of crime in depth.
* **Suggested Future Works:**
  + The paper suggests that the new features (POI and taxi flow) could be incorporated into other crime prediction models, such as those in the "place-centric" paradigm.
  + The significantly better performance with the new urban data could serve as a "new baseline for future crime inference problems".

1. **A Comparative Analysis of Multiple Methods for Predicting a Specific Type of Crime in the City of Chicago", with the research conducted in 2023**

This research paper presents a comparative analysis of different machine learning methods for predicting a specific crime type—theft—in Chicago. The authors' primary goal is to determine how well theft can be predicted using only spatiotemporal information. The study employs and compares the effectiveness of several supervised learning models, including support vector machines (SVM), linear regression, XGBoost, Random Forest, and k-nearest neighbors (KNN). The paper highlights the importance of addressing imbalanced data, a common issue in crime datasets, and uses techniques like SMOTE oversampling and random undersampling to handle it.

The methodology involves data preprocessing, exploratory data analysis (EDA), and feature engineering to prepare the Chicago crime dataset. The models are trained and evaluated using metrics such as F1-score and AUC-ROC. The results show that **XGBoost** achieved the best performance with an **F1-score of 0.86 and an AUC-ROC of 0.87**. The study concludes that spatiotemporal features are a valid approach for predicting crimes of opportunity like theft, and that XGBoost, paired with Shapley Additive Explanations (SHAP) for interpretability, is a highly effective model for this task.

**Paper Details**

* **Title and Year:** "A Comparative Analysis of Multiple Methods for Predicting a Specific Type of Crime in the City of Chicago", with the research conducted in 2023.
* **Dataset Used:** A public dataset from the United States government containing crime information in Chicago from 2001 to 2023. The dataset is a 1.17 GB CSV file with 7,724,493 records and 22 columns. A smaller subset of this data was used for some models due to computational limitations.
* **Approaches/Techniques:**
  + **Data Preparation:** Data cleaning, handling missing values, outliers, and duplications were performed. Features recorded after a crime, such as ID, FBI Code, and Arrest, were removed. New spatiotemporal features like "Week Number," "month," "weekday," and "hour" were created from the Date feature. A KNN-based approach was used to impute missing data.
  + **Models:** The study compared multiple algorithms:
    - K-Nearest Neighbors (KNN).
    - Logistic Regression.
    - Support Vector Machine (SVM).
    - Random Forest.
    - XGBoost.
  + **Addressing Imbalanced Data:** The Synthetic Minority Oversampling Technique (SMOTE) and a random undersampler were used to handle the dataset's imbalance.
  + **Evaluation:** Models were evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.
  + **Interpretability:** Shapley Additive Explanations (SHAP) was used to measure the contribution of each feature to the predictions.
* **Limitations:**
  + The dataset lacked detailed information on the offender (age, ethnicity, profession, criminal history), which could improve prediction accuracy.
  + It is uncertain whether the methods and approaches used are applicable to other countries or major cities.
  + Crime is inherently imbalanced, making it difficult to acquire a perfectly balanced dataset and requiring significant preprocessing time to address imbalances.
  + The study's results are based on a specific type of crime (theft).
* **Suggested Future Works:**
  + Acquiring a dataset with more information on the individuals involved in crimes.
  + Utilizing a deep learning model to see if it significantly impacts prediction results.
  + Applying additional imputation and synthesis techniques to the existing dataset to check for improvements.
  + Comparing the results when predicting less common crime types, such as ritualism

1. **"Forecasting Crime with Deep Learning," published in 2018.**

This paper explores the use of deep neural networks to make fine-grained, next-day crime count predictions for Chicago and Portland. The research augments traditional crime data with external datasets, including weather, census, and public transportation data, to capture a wider range of factors that influence crime. The crime counts are broken into 10 bins, and the model's goal is to predict the most likely bin for each spatial region on a daily basis. The authors test and compare four different neural network architectures of increasing complexity: a simple Feed Forward Network (FFN), a Convolutional Neural Network (CNN), a Recurrent Neural Network (RNN), and a hybrid RNN+CNN model.

The key contributions of this work are the use of a joint recurrent and convolutional neural network for crime prediction, the integration of multiple external datasets, and a focus on daily-level predictions. The study finds that the most complex model, RNN+CNN, achieves the highest accuracy, with 75.6% for Chicago and 65.3% for Portland. The results demonstrate the value of using deep learning and a rich set of external data to improve crime forecasting accuracy. The paper also discusses the impact of different data sources, feature importance, and the effect of beat-level characteristics and weather conditions on model performance.

**Paper Details**

* **Title and Year:** "Forecasting Crime with Deep Learning," published in 2018.
* **Dataset Used:**
  + **Crime Data:**
    - **Chicago:** Roughly 6 million crime records from 2001 onward, containing geographic information (latitude, longitude, beat, district), crime type, and binary fields for arrests and domestic crimes.
    - **Portland:** Calls for service data from a National Institution of Justice challenge, lacking arrest and domestic crime flags.
  + **External Data:**
    - **Weather:** Data from the National Oceanic and Atmospheric Administration, including temperature maximum, minimum, midday temperature, precipitation, snowfall, and snow depth.
    - **Public Transportation:** Chicago Transit Authority (CTA) daily ridership numbers for trains and buses, and station entry numbers. This data was only available for Chicago.
    - **Census:** Data from the 2000 and 2010 U.S. Census, including socioeconomic fields like income, racial makeup, and age.
* **Approaches/Techniques:**
  + **Models:** Four deep neural network architectures were used:
    - **Feed Forward Network (FFN):** The simplest model with multiple layers.
    - **Convolutional Neural Network (CNN):** Used to capture spatial information by treating a city map as an image.
    - **Recurrent Neural Network (RNN):** Specifically, a Long Short-Term Memory (LSTM) network, used to capture temporal dependencies.
    - **Recurrent Convolutional Network (RNN+CNN):** A hybrid model combining both CNN and RNN layers to capture both spatial and temporal aspects of the data.
  + **Data Processing:**
    - Crime counts were aggregated by beat and day and placed into one of 10 bins for classification.
    - A **walk-forward training method** was used, with 9-month training periods and 3-month test periods, to ensure that the models were trained on recent, relevant data.
  + **Evaluation:** Model performance was measured using **classification accuracy** and **Mean Absolute Scaled Error (MASE)**.
* **Limitations:**
  + The Portland dataset was not as rich as Chicago's, lacking fields for arrests and domestic crimes.
  + Public transportation data was not available for Portland.
  + Weather data did not vary much across Chicago, limiting its predictive power.
  + Days with high precipitation or snowfall slightly decreased accuracy, but it's unclear if this is due to inherent unpredictability or fewer training examples for those conditions.
  + The FFN model's engineered temporal and spatial features had "hard limits," making the RNN+CNN model more effective due to its lack of such restrictions.
* **Suggested Future Works:**
  + The paper does not explicitly suggest future works, but its contributions—being the first to use a combined RNN+CNN for this purpose, augmenting with multiple external datasets, and making next-day predictions—imply that further research can build on these foundations.

1. **"Crime Analysis in Chicago City," published in 2019**

This paper, titled "Crime Analysis in Chicago City," analyzes historical crime data from Chicago to identify crime patterns and hotspots using two clustering approaches. The study aims to provide a system that can process large amounts of data to assist law enforcement agencies in making more informed decisions and effectively deploying resources.

**Paper Details**

* **Title and Year:** "Crime Analysis in Chicago City," published in 2019.
* **Dataset Used:** Crime data from the Chicago Data Portal, spanning two years from 2010-2012, when Chicago had a high crime rate.
* **Approaches/Techniques:** The research followed two main clustering approaches to analyze crime patterns:
  + **K-means clustering:** The authors used the WEKA tool with the Euclidean distance metric to group similar crimes and identify crime locations. An ideal number of 6 clusters was determined using the sum of squared errors (SSE) method.
  + **Spatial clustering:** The SatScan software was used to perform spatial analysis and detect crime hotspots by identifying areas with high and low crime rates using a Poisson model.
  + **Data preprocessing:** This involved cleaning raw data, removing missing values, normalizing data, and aggregating functions using SQL queries to prepare the necessary input files for the tools.
  + **Validation:** The results from both clustering approaches were cross-checked with "ground truth" information from news reports and government websites to validate findings about specific neighborhoods and wards.

**Limitations**

* The research relies on historical data and does not provide real-time tracking or prediction.
* The previous research cited in this paper had limitations, including the inability to predict crime hotspots for a specific time window and a simple mapping method.
* The accuracy of spatial clustering heavily depends on the design and optimization of the attribute taxonomy.

**Suggested Future Works**

* The authors would like to perform more **Spatial Temporal mining** to allow for the effective deployment of police resources for any given window of time.
* The development of a more robust Crime Data Information System is suggested, capable of performing **association analysis** and **prediction** on datasets.
* Future work could also explore mining applications for **audio files and image data** to identify vehicles, people, and unique characteristics of criminals.

1. **"Deep Learning Based Crime Prediction Models: Experiments and Analysis", a preprint from July 2024**

This paper presents a comprehensive experimental analysis of seven state-of-the-art deep learning models for crime prediction. The research addresses a significant gap in the literature, as previous studies often compared their models against only one or two other deep learning models and lacked uniform experimental settings. The authors categorize and evaluate the models based on variations in a region's size, crime density, and the temporal granularity of predictions.

The study uses 2019 Chicago crime data, augmented with external features like Point of Interest (POI), taxi flow, and public service complaint data. The models are tested on two primary tasks:

**regression** (predicting the number of crimes) and **classification** (predicting whether a crime will occur). For regression, models that capture interactions between external features and crime data perform better when data is sparse, while models using a homophily-aware graph benefit from denser crime data. For classification, models that explicitly capture recent, daily, and weekly temporal trends perform best across all scenarios. AIST and HAGEN are consistently identified as the top-performing models in most scenarios, with AIST excelling in regression's Mean Average Error (MAE) and classification, and HAGEN performing better in regression's Rooted Mean Square Error (RMSE) metric. The research concludes by providing recommendations for designing future deep learning-based crime prediction models.

**Paper Details**

* **Title and Year:** "Deep Learning Based Crime Prediction Models: Experiments and Analysis", a preprint from July 2024.
* **Dataset Used:**
  + **Crime Data:** 2019 Chicago crime data for theft, criminal damage, battery, and narcotics.
  + **External Data:** 311 public service complaint data, POI data, and taxi trip data from Chicago, all from 2019.
* **Approaches/Techniques:**
  + **Models Evaluated:** A comprehensive set of seven major deep learning models: DeepCrime (DC), MiST, CrimeForecaster (CF), HAGEN, ST-SHN, ST-HSL, and AIST.
  + **Evaluation Metrics:**
    - **Regression:** Mean Average Error (MAE) and Rooted Mean Square Error (RMSE).
    - **Classification:** Macro-F1 and Micro-F1 scores.
  + **Experimental Criteria:** Experiments were categorized to evaluate performance based on:
    - The area of the target region (very small, small, medium, large, very large).
    - Crime density (very low, low, medium, high, very high).
    - Temporal granularity of predictions (4 hours, 6 hours, 12 hours, 24 hours).
  + **Model Components:** The study analyzed how different models capture **categorical, spatial, and temporal dependencies**. Models like CrimeForecaster, HAGEN, and AIST use graph neural networks for spatial interactions, while ST-SHN and ST-HSL use hypergraphs. Recurrent networks like GRU and LSTM capture temporal dependencies.
  + **External Features:** The impact of external datasets was explored through an ablation study.
* **Limitations:**
  + A significant research gap existed because no longitudinal study compared all major deep learning models in a unified setting.
  + Previous models often failed to address how performance changes with varying crime data density, region area, or prediction time intervals.
  + The study focuses solely on Chicago, but claims its methodology of grouping communities can capture properties of other cities like Los Angeles and New York.
* **Suggested Future Works:**
  + The authors provided a set of **recommendations (R1-R5)** for designing future deep learning models.
  + **R1 (Spatio-temporal correlation):** Models should explicitly capture both spatial correlations (including those with non-neighboring regions with similar crime profiles) and temporal correlations (daily, weekly).
  + **R2 (Absence of external features):** In cases where external features are unavailable, a good starting point is a combination of GNNs (GCN, GAT) and RNNs (LSTM, GRUs) to capture spatial and temporal correlations.
  + **R3 (Utilizing external features):** If external features are used, models should include explicit modules to capture the interaction between crime data and these features to fully benefit from them.
  + **R4 (Regression-only task):** The spatial module should be the driving force, designed to learn from both neighboring and non-neighboring regions that exhibit similar crime patterns.
  + **R5 (Classification-only task):** The temporal module is paramount, with separate modules to capture recent, daily, and weekly trends. Spatial and external feature modules should be introduced to complement the temporal module.

1. **"The Windy City's Dark Side: A Statistical Exploration of Crime in the City of Chicago" , published on July 4, 2024.**

This paper provides a detailed statistical exploration of crime trends in Chicago from 2001 to 2023, using a publicly available crime database from the Chicago Police Department. The study's primary goal is to shed light on the patterns, distribution, and variations in crime across different types and locations through advanced data analytics and visualization techniques. Using exploratory data analysis (EDA), the researchers identified significant insights, such as the prevalence of theft and battery, the impact of seasonal changes on crime rates, and the spatial concentration of criminal activities. The study also examines case clearance rates, revealing that only 26% of total crimes resulted in an arrest, with wide variations across different crime categories. The research leverages a Power BI dashboard to visually represent crime data, making complex patterns easier to understand and enabling dynamic interaction with the dataset. The paper concludes with recommendations for enhancing public safety strategies and suggests directions for future research.

**Paper Details**

* **Title and Year:** "The Windy City's Dark Side: A Statistical Exploration of Crime in the City of Chicago" , published on July 4, 2024.
* **Dataset Used:** The "Crimes: 2001 to Present" dataset from the City of Chicago's official data portal. It contains over 7.9 million crime records from January 2001 to the present.
* **Approaches/Techniques:**
  + **Data Collection:** The primary dataset was sourced from the City of Chicago's official data portal.
  + **Data Preprocessing:** The data was cleaned to rectify inconsistencies, missing values, and anomalies. Data transformation was performed to standardize dates, times, and categorical variables, and to aggregate crime incidents by type, location, and time.
  + **Exploratory Data Analysis (EDA):** This was the foundation of the investigation, using statistical tools and visualizations to uncover patterns and relationships in the data. EDA included temporal analysis (annual, monthly, weekly, hourly patterns), spatial analysis (mapping crime incidents to identify hotspots), and type-specific analysis (classifying crimes to find the most prevalent categories).
  + **Visualization:** A Power BI dashboard was developed to create interactive visualizations like heat maps, trend lines, and bar charts to make the complex data digestible.
* **Limitations:**
  + **Data Accuracy:** The study relies on publicly available data, which may suffer from underreporting, data entry errors, or inconsistencies due to changes in reporting standards over time.
  + **Geospatial Constraints:** The geographic information may be generalized or imprecise, which limits the accuracy and depth of spatial analysis at a micro-level.
  + **Temporal Limitations:** The analysis is historical (2001-2023) and may not fully capture the long-term effects of recent societal changes, such as the COVID-19 pandemic.
  + **Clearance Rate Interpretation:** The clearance rates based on arrests may not fully represent the complexity of case resolutions, including prosecutions and convictions.
* **Suggested Future Works:**
  + **Integrate additional datasets:** Future studies could incorporate socioeconomic indicators, police deployment data, and community resource information to explore the multifaceted drivers of crime.
  + **Longitudinal and comparative studies:** Extending the analysis beyond 2023 would allow for the examination of emerging crime trends and the long-term impact of interventions. Comparative studies with other cities could provide insights into different crime prevention strategies.
  + **Micro-level geographic analysis:** Using more granular geographic data, where available, could lead to more targeted interventions.
  + **Qualitative research:** Incorporating interviews with law enforcement and community leaders could provide deeper insights into contextual factors.
  + **Technology-driven prediction models:** The development and application of advanced predictive analytics and machine learning models could offer new perspectives for anticipating crime occurrences.
  + **Impact assessment:** Rigorous evaluations of specific policing strategies and community programs could clarify their effectiveness.

1. **"Real Time Violence Detection and Alert System," published in March 2024.**

This paper proposes a real-time violence detection and alert system that uses artificial intelligence to identify potential violent incidents from surveillance video feeds. The system is designed to provide a rapid response to such incidents by automatically analyzing video frames, detecting violent patterns, and sending alerts to security personnel or law enforcement. The core of the system is a deep learning model based on a Convolutional Neural Network (CNN). To ensure better accuracy and reduce computational time, the system uses a lightweight, pre-trained MobileNetV2 model instead of an independent CNN.

The system's methodology involves several steps: a dataset of 1,000 videos (half violent, half non-violent) is collected and pre-processed. A violence recognition model based on MobileNetV2 is trained to detect violent patterns. When a violent activity is detected, relevant frames are extracted and enhanced. Face detection is then performed using MTCNN. If 30 consecutive frames are classified as violent, an alert is triggered and sent via a Telegram bot. The alert includes the time, location, a captured image, and a short video clip of the incident. Experiments show that the MobileNetV2 model achieved a training accuracy of 96.2% and a testing accuracy of 94.86%.

**Paper Details**

* **Title and Year:** "Real Time Violence Detection and Alert System," published in March 2024.
* **Dataset Used:** A dataset of 1,000 videos, with an equal number of violent and non-violent videos, primarily sourced from public CCTV cameras. The video clips last about five seconds on average.
* **Approaches/Techniques:**
  + **Model Architecture:** The core of the system is a deep learning model for automatic violence detection based on a Convolutional Neural Network (CNN). A lightweight, pre-trained MobileNetV2 model is used to improve accuracy and reduce computation time.
  + **Preprocessing:** The dataset is pre-processed using methods such as image resizing, normalization, and augmentation.
  + **Alert Generation:** If a counter identifies 30 consecutive frames as violent, an alert is sent via a Telegram bot. The alert includes a captured image, a short video clip, and details like the date, time, and location of the incident.
  + **Visualization:** Enhanced images and violence alerts are stored in a Firebase database for record-keeping and future review. Face detection is performed on these images using MTCNN and Pyplot.
* **Limitations:** The provided document does not explicitly list any limitations for the proposed system itself. However, a related work review mentions that a spatiotemporal modeling approach using 2D CNN is not suitable for moving cameras and incurs high computational costs due to its use of three modules. Another related work review notes that a 3D CNN-based approach is computationally expensive and not suitable for real-time, daily use.
* **Suggested Future Works:**
  + The model could be enhanced to function across multiple interconnected cameras simultaneously.
  + Audio and other sensor data could be integrated to improve detection precision and contextual insight.
  + The system could incorporate emotion data from videos to help distinguish between harmless actions and genuine threats.
  + Feature extraction methods could be augmented to include additional elements in the deep learning framework for a more thorough violence detection approach.
  + The importance of ethical deployment and privacy safeguards should be emphasized.

1. **“Real-Time Violence Detection Using CNN-LSTM," published in April 2021**

This paper proposes a pseudo-real-time violence detection system that uses a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model to identify violent activities in video feeds. The model's primary goal is to alert authorities when violence is detected with the highest possible accuracy. The author focuses on extracting meaningful information from CCTV video feeds and hypothesizes a signaling mechanism to prioritize which videos receive computation, thereby reducing system overhead. The proposed model uses a pre-trained CNN (ResNet50) as a feature extractor, with its final dense layers removed. The extracted features are then fed into an LSTM layer to capture temporal relationships. The system also includes data preprocessing steps, such as frame-to-frame differencing and augmentation, to enhance and expand the training data. The model's performance was evaluated on three datasets: Hockey Fight, Movies, and Violent-Flows, with the best overall accuracy reaching 91.4% on the Violent-Flows dataset and 100% on the Movies dataset. The study also compares the CNN+LSTM approach to a Pose Estimation+LSTM approach, finding that CNN+LSTM is more accurate and faster.

**Paper Details**

* **Title and Year:** "Real-Time Violence Detection Using CNN-LSTM," published in April 2021.
* **Dataset Used:**
  + **Hockey Fight Dataset:** Contains an equal number of violent and non-violent clips of hockey players fighting.
  + **Movies Dataset:** Consists of an equal number of violent and non-violent clips from movies.
  + **Violent-Flows Dataset:** A collection of crowd violence videos, primarily from football matches.
* **Approaches/Techniques:**
  + **Primary Model:** A hybrid **CNN+LSTM** approach is used to detect violence. A pre-trained CNN (ResNet50) extracts features from video frames, and these features are fed into an LSTM layer to learn temporal patterns.
  + **Comparison Model:** The CNN+LSTM approach is compared against a **Pose Estimation+LSTM** method.
  + **Data Preprocessing:**
    - Videos are sampled into batches of 20 consecutive frames.
    - Frame-to-frame differencing is used to capture spatial movement.
    - Data augmentation techniques like cropping and transposition are applied to enrich the dataset.
    - A classic 80-20 split is used for training and testing data.
  + **Hyperparameter Tuning:** The CNN architecture type (ResNet50, InceptionV3, VGG19), learning rate, number of frames, augmentation use, and dropout rate are evaluated to optimize the model.
  + **Inference Algorithm:** The author hypothesizes a priority-based scheduling algorithm to efficiently assign computation to video streams, based on the probability that violence may occur.
* **Limitations:**
  + The system is described as "pseudo real time" rather than truly real time, especially when drawing inferences, despite the use of distributed computing.
  + The dropout layer did not improve model performance in this specific experimental setup, possibly because the datasets are domain-specific.
  + The study was limited by low GPU power, which may have affected the training period and accuracy, particularly for the Hockey dataset.
  + The approach may struggle to generalize to more complex, heterogeneous video files with different qualities, camera positions, and scenes.
* **Suggested Future Works:**
  + Incorporate audio inference into the system using fuzzy logic to combine results from both video and audio data for a better inference.
  + Implement a priority-based scheduling algorithm to efficiently assign computational tasks to video streams based on the probability of future violence.
  + Develop creative solutions for data collection, advanced generalization techniques, and real-time optimizations to handle more complex violence scenarios.
  + Achieve a true "real time inference milestone" in future iterations of the research.