

1.1 Introduction

Crime remains a significant societal concern, necessitating effective methods for identifying and monitoring criminal activities to prevent future offenses [1]. Traditional crime detection techniques, such as eyewitness accounts and physical evidence analysis, have limitations in reliability. Recently, there has been an increased focus on leveraging sensor data for crime detection and offender tracking, suggesting more innovative and potentially accurate approaches to crime identification [2; 3]. Sensors gather information about the environment and human interactions within it. Analysis of this data can reveal patterns potentially associated with criminal behavior [4]. For example, tracking movement patterns may highlight unusual or suspicious activities [5]. This information aids in identifying potential crimes and enhancing prevention efforts, making sensor data a valuable tool for improving community safety [6]. Several advantages support the use of sensor data for crime detection and criminal monitoring [7]. Real time data availability enables swift perpetrator identification [8]. Additionally, it facilitates long distance tracking, complicating evasion attempts [9]. Furthermore, identifying crime-related patterns in the data can assist in apprehending offenders and reducing recidivism [10]. This thesis explores patterns in sensor data for crime detection and post crime offender tracking [11]. This section introduces the topic and discusses the potential applications of mobile phone sensor data for the proposed project. The subsequent section will delve into the project's relevance in the context of current technological capabilities [12].

1.1.1 The Relevance of the Project

Combating criminal activities in contemporary society poses significant challenges, particularly when there is insufficient communication between law enforcement and the public [13]. Often, police may lack complete awareness of ongoing incidents in their jurisdiction, while citizens may not actively engage in crime detection efforts [14]. To address this issue, fostering citizen involvement and increasing public awareness of criminal activities is crucial for developing a safer and more secure community [15].

The development of a specialized application could provide a unified platform for effective communication between citizens and law enforcement [16]. Rather than transmitting data to cloud servers for processing, this application could store

information directly on mobile devices, similar to aircraft black boxes [17]. Subsequently, law enforcement could utilize this stored data for crime identification and investigation. This approach enables smart devices to efficiently detect criminal activities, aligning with the smart cities initiative launched by the Indian government in 2015 to combat various forms of societal crime [18].

This thesis seeks to reconstruct events preceding law enforcement's arrival at a crime scene. Mobile phone data can significantly aid in crime resolution and securing justice for victims [19]. Additionally, it can assist individuals wrongly accused by providing impartial and reliable information [20]. By integrating public participation and sensor technology, we can establish a more effective approach to crime prevention in our communities [21].

Having established the project's significance, the next phase involves exploring various categories of potential criminal activities [22].

Criminal activities can be classified into various categories based on their nature and impact (as illustrated in Figure 1.1). Some prevalent categories include:

- **Offenses Against Persons:** These involve physical force or threats against individuals, such as homicide, assault, robbery, sexual assault, and domestic abuse [23].



Fig. 1.1: Classification of criminal activities

- **Offenses Against Property:** These crimes involve unlawful interference with others' possessions [24]. Examples include burglary, larceny, arson, vandalism, and trespassing.
- **Economic Offenses:** These typically involve illicit activities related to financial gain or fraud [25]. Examples include embezzlement, money laundering, identity theft, fraud, bribery, and tax evasion.
- **Digital Offenses:** These are crimes committed using digital technologies [26]. This category encompasses hacking, phishing, online fraud, digital identity theft, cyberstalking, and malware distribution [27].
- **Substance-Related Offenses:** These involve the illicit possession, production, distribution, or trafficking of controlled substances [6; 28].
- **Corporate Malfeasance:** These non-violent offenses are committed in professional or business contexts. Examples include fraud, insider trading, bribery, forgery, and embezzlement.
- **Bias-Motivated Offenses:** These are committed against individuals or groups based on protected characteristics such as race, religion, ethnicity, gender, or sexual orientation.

- **Syndicated Criminal Activities:** These involve organized groups engaging in large-scale illegal operations, such as drug trafficking, human trafficking, smuggling, money laundering, and racketeering.
- **Sexual Offenses:** These involve non-consensual sexual acts or offenses of a sexual nature, including sexual assault, harassment, child sexual abuse, and indecent exposure.
- **Traffic Violations:** These include infractions of traffic laws and regulations, such as speeding, reckless driving, driving under the influence (DUI), hit- and-run incidents, and driving without a valid license.

It's worth noting that these categories may overlap, and there can be additional subcategories or specific types of offenses within each broader classification. Having explored various categories of criminal activities, we now turn our attention to the technological aspects of crime identification. We will begin by examining IoT technology, which involves the transmission or storage of sensor data using wireless communication methods.

1.1.2 Internet of Things (IoT)

While IoT has been a focus of research for many years, recent advancements in electronics and software have transformed it from concept to reality. A key enabler has been the development of cost-effective, low-power sensors suitable for widespread deployment. Furthermore, the evolution of diverse protocols has dramatically improved sensor-to-cloud connectivity and data transmission rates. The proliferation of cloud platforms has further accelerated IoT adoption by providing robust data storage and processing capabilities. Concurrently, progress in machine learning has revolutionized data analysis. Sensor-collected information is no longer merely transmitted to users; instead, machine learning algorithms analyze this data to generate tailored feedback and solutions. The convergence of IoT and artificial intelligence has spawned innovative technologies like voice-controlled digital assistants, capable of processing user commands and managing various



Fig. 1.3 : Smart wearables monitoring vital signs, activity levels, and other physiological data

during different activities. As a result, digital traces of our lives are dispersed across IoT databases, potentially providing valuable clues for solving complex cases. The data collected through IoT devices is numerical in nature, shifting the paradigm of evidence from subjective human accounts to objective, data-driven records. However, protecting personal data privacy remains a significant challenge for future IoT forensic studies. Unlike traditional forensics, where evidence is obtained through legal channels and handled securely, IoT forensics gathers data directly from users' devices. Therefore, stringent measures must be implemented to protect collected information until authorized access is granted. As illustrated in Figure 1.3, sensor-equipped smartwatches have become ubiquitous, continuously monitoring vital signs, physical activities, and even stress levels. The temporal and spatial metadata associated with this information makes it invaluable evidence in criminal investigations. Additionally, devices like CCTV cameras contribute to data collection, capturing footage of criminal activities that can be securely stored in cloud environments for future investigative purposes. The significance of IoT forensics extends beyond advanced sensor technology to the development of sophisticated analysis algorithms. Machine learning techniques now enable automated analysis of collected data, providing crucial evidence to streamline crime-solving processes. In

the context of this thesis, IoT plays a fundamental role in facilitating the collection, analysis, and real-time transmission of sensor data. It connects a diverse array of sensors and devices, from everyday objects to complex industrial machinery, through wireless Internet communication. This interconnected network enables seamless data exchange and remote control capabilities. The widespread adoption of IoT amplifies the potential for utilizing sensor data in crime detection and tracking. Strategically placed IoT enabled sensors in public spaces, buildings, and personal devices can continuously monitor environmental changes and human activities. For example, surveillance cameras, GPS trackers, and acoustic sensors can provide critical insights into individual movements and actions, which may be instrumental in detecting criminal behavior. Moreover, the ubiquity of IoT has expanded the scope of real-time data collection. As the number of connected devices grows, law enforcement agencies can access data from multiple sources simultaneously, enhancing their ability to respond promptly to criminal incidents. This real-time data availability is particularly valuable for post-crime detection, allowing authorities to swiftly gather crucial evidence and make informed decisions in tracking and apprehending suspects. Furthermore, IoT's cost-effectiveness and efficiency make it a valuable tool for this application. The ability to program IoT devices with minimal human intervention reduces the need for constant monitoring, streamlining data collection and analysis processes. This allows law enforcement to focus on interpreting the patterns and trends identified through sensor data pattern analysis. Having explored IoT technology, we will now examine recurrent neural networks, a specialized deep neural network method. This artificial intelligence based technique is well-suited for effectively processing IoT sensor data.

Figure 1.4 presents the user interface of the 'IoTool' mobile application, an existing tool employed in the initial stages of our proposed methodology development. The application displays real-time data in both graphical and numerical formats, enabling users to easily monitor and analyze various sensor readings, including posture, acceleration, and electrocardiogram (ECG) data. The image depicts a smartphone screen showcasing the 'IoTool' application interface. The upper portion of the display

features a line graph illustrating fluctuating ECG

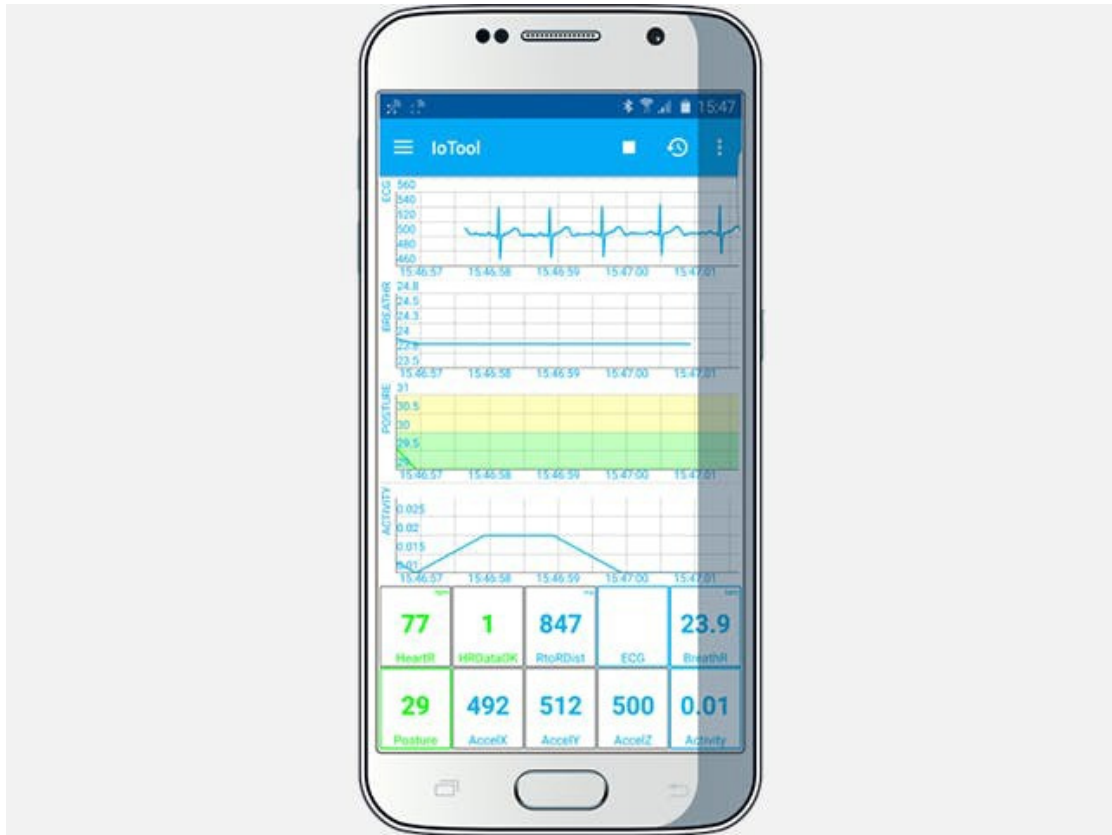


Fig. 1.4 : 'IoTool' Mobile Application Interface for Sensor Data Acquisition

values over time. Below the graph, a section presents numerical values derived from various sensors, which may include pressure sensors, accelerometers, and barometers, depending on the specific mobile device model. The application's interface incorporates blue and green text against a contrasting background, with gray lines forming a table at the bottom of the screen. The green color is used to indicate values that fall within acceptable ranges. 'IoTool', a pre-existing mobile application, is designed for the acquisition and monitoring of mobile sensor data. It presents real-time information through both graphical representations and numerical displays, allowing users to track and analyze various sensor readings. The image showcases the application's interface, which provides dynamic data visualization through graphs and numerical values. The upper section of the screen features a line graph depicting data variations over time, with each set of data points timestamped to facilitate real-time monitoring.

1.2 Sensors in Mobile Devices

Modern mobile devices incorporate a wide array of sensors designed to collect data about the device's surroundings and user interactions. These sensors form the basis for numerous functionalities, ranging from automatic screen orientation to activity tracking. Common sensors include the accelerometer, which measures acceleration in three dimensions for screen rotation and activity monitoring purposes. The gyroscope detects rotational rates around different axes, contributing to image stabilization in cameras and supporting augmented reality applications. Magnetometers measure the strength and direction of the Earth's magnetic field, aiding in compass functionality and augmented reality features. Proximity sensors detect nearby objects, enabling actions like screen deactivation during calls or preventing accidental touches. Ambient light sensors measure environmental light levels, facilitating screen brightness adjustments and enabling features like automatic night mode for battery conservation. Fingerprint sensors authenticate users through fingerprint scans, enabling secure device unlocking, payments, and app access. Heart rate sensors measure users' pulse rates for applications ranging from fitness tracking to stress monitoring and health insights. These sensors represent only a subset of the extensive sensor suite present in mobile devices. As technology advances, the integration of additional sensors is expected, unlocking new features and capabilities.

1.2.1 Accelerometer

The accelerometer (illustrated in Figure 1.5) is a vital sensor in mobile devices, measuring acceleration - the rate of change in velocity. Its applications are diverse and essential to various smartphone functionalities. Primarily, accelerometers enable automatic screen rotation by detecting changes in device orientation, allowing smooth transitions between portrait and landscape modes. These sensors also contribute significantly to health and fitness tracking, quantifying steps taken, distance traveled, and calories expended, aiding users in achieving their fitness goals. Accelerometers play a crucial role in recognizing motion gestures, enhancing user interaction with

apps through actions like shaking or tilting the device. Their

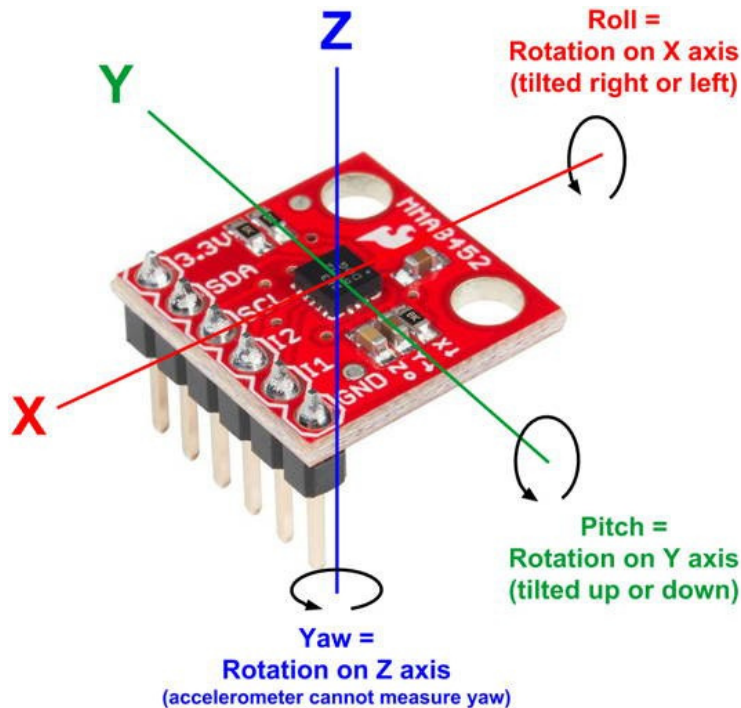


Fig. 1.5: Accelerometer

utility extends to gaming, where tilt movements control actions such as steering in racing games or aiming in shooting games. In virtual reality (VR) and augmented reality (AR) applications, accelerometers track head movements, synchronizing virtual or augmented elements with user actions. Despite their compact size and low power consumption, accelerometers enable features that have become integral to mobile device functionality. These sensors typically consist of a small mass suspended on a spring; device movement causes the mass to move relative to the spring, and the sensor converts this motion into an electrical signal. The device's software processes this signal to determine orientation and movement. As versatile and essential components, accelerometers are likely to continue shaping mobile technology's future, with their impact expected to expand further.

The accelerometer chip depicted in Figure 1.6 is a miniature sensor that measures a phone's acceleration across three axes. This versatile component serves multiple purposes:

1. **Movement Detection:** It monitors the phone's movements, enabling control in various applications and games by responding to tilting or shaking motions.



Fig. 1.6 : Magnified view of an accelerometer chip on a mobile phone motherboard

2. **Posture Recognition:** The accelerometer determines the phone's orientation (e.g., vertical or horizontal), facilitating automatic screen rotation and enhancing contextual interactions in applications and games.
3. **Pedometer Function:** By utilizing the accelerometer's capabilities, the device can count the user's steps, supporting fitness tracking and progress monitoring.
4. **Drop Recognition:** The sensor can detect when the phone is falling, potentially triggering alarms or notifications to alert designated contacts.

Accelerometers have become fundamental components in contemporary mobile phones, introducing innovative interaction methods, spurring technological advancements, and significantly improving overall user experience and convenience.

1.2.2 Gyroscope

The gyroscope (illustrated in Figure 1.7) is a crucial sensor in contemporary mobile devices that measures rotational motion around three axes—pitch, roll, and yaw.

Utilizing microelectromechanical systems (MEMS) technology, mobile phone gyroscopes employ minuscule vibrating masses that resonate at specific frequencies. When the phone rotates, these vibrations are altered, providing precise measurements

of angular motion. Gyroscopes contribute significantly to various aspects of mobile device functionality:



Fig. 1.7 : Gyroscope

- **Screen Orientation:** Gyroscopes enable automatic screen rotation between portrait and landscape modes based on the device's tilt, enhancing the viewing experience.
- **Motion Detection:** By tracking the phone's movements, gyroscopes facilitate motion-controlled games and applications, allowing users to interact through tilting, rotating, or shaking the device.
- **Camera Stabilization:** Gyroscopes play a vital role in reducing image blur and ensuring smoother video capture, particularly in low-light conditions or during motion.
- **AR and VR Applications:** These sensors are essential for augmented reality (AR) and virtual reality (VR) experiences, providing real-time tracking of the device's orientation in three-dimensional space.
- **Location and Navigation:** Gyroscopes assist navigation apps by providing accurate directional and orientation data, especially in areas with poor or no GPS coverage.

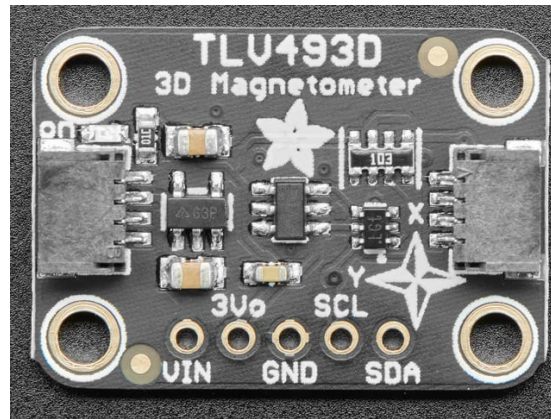


Fig. 1.8 : Magnetometer

- **Gesture Recognition:** These sensors enable gesture-based controls, allowing users to interact with devices or applications through specific movements.
- **Device Positioning:** Gyroscopes provide precise orientation data, enabling the phone to adjust settings or interfaces based on its position, such as switching between left-hand and right-hand modes.
- **Activity Monitoring:** In fitness tracking applications, gyroscopes contribute by monitoring user movements during exercise or physical activities, offering detailed motion data.

Gyroscopes are indispensable components in modern mobile devices, enhancing user experience, enabling innovative features, and driving advancements in mobile technology.

1.2.3 Magnetometer

The magnetometer (depicted in Figure 1.8) is an instrument that measures the intensity and orientation of magnetic fields. It plays a crucial role in mobile devices, particularly for determining device orientation and providing compass functionality, which are essential for augmented reality applications and location based features.

Most mobile phone magnetometers operate based on the Hall effect, utilizing a current carrying conductor within a magnetic field. This interaction induces a voltage change, which can be measured to determine the magnetic field's strength and direction. The magnetometer's applications in mobile phones are diverse:

It serves as the primary sensor for compass applications. It facilitates orientation tracking for automatic screen rotation and augmented reality features. It enhances

location awareness by complementing GPS data, especially in areas with poor GPS reception. It enables metal detection capabilities, allowing applications to locate hidden objects or buried items. It contributes to gesture recognition, detecting device movements for hands-free interactions. It aids in environmental monitoring, detecting changes in the Earth's magnetic field that may indicate phenomena like seismic activity. As a versatile and powerful sensor, the magnetometer's importance is likely to increase with technological advancements, promising novel applications in the evolving landscape of mobile devices. Its ability to provide precise orientation data and interact with the environment positions it as a key component in future mobile innovations.

1.2.4 Ambient Light Sensor

The ambient light sensor (ALS) is a compact electronic component essential to mobile phones and other digital devices. It measures the surrounding light levels and communicates this data to the device's operating system. The system then uses this information to dynamically adjust the screen brightness, optimizing viewing comfort. The primary function of the ALS in a mobile phone is to enhance user experience by preventing excessive screen brightness in low-light environments, thus reducing eye strain, while ensuring adequate visibility in bright conditions. Moreover, the sensor aids in battery conservation by lowering screen brightness when high luminosity is unnecessary, acknowledging that the backlight is a significant power consumer in mobile devices. Mobile phones typically employ one of two main types of ambient light sensors: phototransistors or photodiodes, both effective in measuring light intensity. The sensor is usually located near the front facing camera or earpiece to ensure unobstructed and accurate light measurement. The advantages of ambient light sensors include:

Enhanced user experience through automatic brightness adjustments
Reduced eye strain in varying light conditions
Improved screen visibility across different environments
Extended battery life through intelligent power management
Support for features like automatic night mode activation.

These benefits collectively contribute to an overall improvement in mobile phone functionality and user satisfaction. As mobile technology continues to evolve, the role

of ambient light sensors is likely to expand, potentially enabling more sophisticated light-based interactions and energy-saving features.

1.2.5 Fingerprint

Modern smartphones commonly incorporate fingerprint sensors as a secure and user friendly authentication method. These sensors detect the unique patterns of ridges on a user's fingertip and compare them to a prestored template. Mobile devices typically employ one of three sensor types: optical, which capture visual fingerprint images; capacitive, which detect electrical differences between ridges and valleys; and ultrasonic, which create 3D fingerprint maps using sound waves. The authentication process generally involves placing a finger on the sensor, which then captures the fingerprint data and compares it to the stored reference. Fingerprint sensors offer benefits such as ease of use, enhanced security, and rapid operation. However, they may also present challenges including potential costs, accuracy variations under certain conditions, and vulnerability to spoofing attempts. Despite these limitations, fingerprint sensors are becoming increasingly common in mid-range and premium smartphones, with expectations of continued growth in adoption.

1.2.6 Heart rate sensor

Mobile phone heart rate sensors measure pulse rate, providing data on beats per minute. These sensors, often used for fitness tracking, employ photo plethysmography (PPG), a noninvasive optical method that detects blood volume changes beneath the skin surface. The sensor emits light, typically green or infrared, and measures the reflected light, which varies with each heartbeat. While accuracy can be influenced by factors such as sensor quality, placement, ambient lighting, and skin tone, mobile heart rate sensors generally provide readings within a few beats per minute of actual heart rate, though accuracy may decrease during physical activity. These sensors offer benefits including fitness monitoring, stress level assessment, health insights, cardiovascular disease prevention, and sleep quality analysis. To use a heart rate sensor, users typically install a health or fitness application, ensure the sensor is clean, place it correctly on dry skin, and minimize movement during measurement, particularly when monitoring stress levels in a calm setting.

1.2.7 Barometer

A barometer sensor in mobile devices measures atmospheric pressure, enabling altitude determination, weather condition tracking, and indoor navigation assistance. These sensors function by measuring the atmospheric force on a flexible membrane, typically composed of silicon or MEMS materials. Pressure changes cause membrane deflection, which is converted to an electrical signal and processed to determine atmospheric pressure. Barometer sensors are highly precise, capable of measuring pressure within a few millibars, making them valuable in mobile devices. They serve multiple functions, including altitude estimation for fitness and navigation applications, monitoring weather changes for forecasts, and facilitating indoor navigation by detecting floor level changes. The inclusion of barometer sensors improves GPS accuracy, particularly in areas with poor signal reception, reduces power consumption due to their energy-efficient nature, and enhances user experience through more accurate altitude measurements, improved indoor navigation, and better weather predictions. As this technology advances, its applications in mobile devices are expected to expand further.

1.2.8 Global Positioning System (GPS)

The Global Positioning System (GPS) is a satellite based navigation network providing location and time data to receivers worldwide, given an unobstructed view of at least four GPS satellites. It is a fundamental component in modern mobile devices, enabling numerous features and applications. Mobile phone GPS utilizes trilateration to determine location by calculating distances from orbiting GPS satellites. The system consists of 24 satellites orbiting at approximately 20,200 kilometers, each broadcasting signals containing precise location and time information. The phone's GPS receiver captures these signals and computes distances to multiple satellites based on signal travel time. Trilateration with data from at least three satellites determines the phone's position at the intersection of their spheres. A fourth satellite enhances accuracy by correcting errors from factors like atmospheric interference. The GPS receiver continuously updates the device's location in real-time, enabling features such as navigation and fitness tracking. Assisted GPS (A-GPS) improves performance by incorporating cellular network or Wi-Fi data, facilitating faster and more accurate signal acquisition, particularly in weak signal

environments. GPS technology has transformed mobile phone functionality, enabling turn-by-turn navigation, location-based services, fitness monitoring, emergency location services, geotagging, augmented reality applications, and uses in delivery, logistics, wildlife tracking, conservation, and asset management. These applications demonstrate the significant impact of GPS technology on mobile devices and everyday life.

1.2.9 Near Field Communication (NFC)

Near Field Communication (NFC) is a short-range wireless technology enabling communication between devices in close proximity. Based on RFID technology, NFC offers improved data transfer rates and enhanced capabilities.

In mobile phones, NFC serves various functions. It facilitates contactless payments, providing a secure and convenient alternative to traditional methods. NFC also enables rapid data exchange between compatible devices, allowing seamless file transfers. Additionally, it supports tag reading, permitting phones to interact with NFC enabled objects like posters or advertisements for quick information access.

NFC plays a crucial role in access control systems, offering a secure alternative to conventional methods for controlling physical access. Operating at 13.56 MHz with a maximum data transfer rate of 848 kbps, NFC devices can be active or passive, with mobile phones typically functioning as passive devices.

To ensure data security, NFC employs encryption. The NFC Forum, an industry consortium, governs NFC standards and promotes its widespread adoption. Overall, NFC is a versatile technology gaining popularity in mobile phones for its applications in secure payments, efficient data sharing, and interactive functionalities.

1.2.10 Humidity Sensor

Humidity sensors in mobile devices measure atmospheric water vapor concentration, offering various features and functions. Their primary role involves measuring ambient humidity levels, presenting this data via weather apps, or triggering actions like activating air conditioning or dehumidifiers. These sensors also enhance the accuracy of other phone sensors, such as compensating for humidity's impact on temperature readings.

Furthermore, humidity sensors can detect condensation, potentially preventing water damage by initiating protective measures like deactivating the flashlight or camera. The multifaceted contributions of these sensors significantly improve the user experience on mobile devices. As technology advances, the potential for innovative applications in this area is likely to expand.

1.2.11 Ultrasonic sensors

Ultrasonic sensors, also known as ultrasonic transducers, emit and detect high frequency sound waves beyond human hearing range. In mobile phones, they serve critical roles in proximity sensing, gesture recognition, and 3D mapping.

For proximity sensing, these sensors ensure the screen turns off during calls when the phone is near the user's ear, preventing accidental touches and conserving battery. Ultrasonic sensors excel in this role, accurately detecting nearby objects even in low light or screen covered conditions.

In gesture recognition, ultrasonic sensors allow users to control their phones with hand movements, enhancing hands-free functionality. For 3D mapping, these sensors create detailed environmental maps, crucial for augmented reality applications and precise interactions with virtual elements in real-world settings.

Ultrasonic sensors surpass other types by being less prone to interference, maintaining reliability across diverse environments. Their ability to operate through materials like plastic and glass enables seamless integration into phone designs. As technology progresses, ultrasonic sensors are poised to play an increasingly significant role in shaping innovative features, enhancing user experience, and advancing mobile technology.

1.2.12 Deep Learning

Deep learning is an artificial intelligence (AI) approach inspired by the brain's structure and function. It utilizes multi-layered artificial neural networks (ANNs) to discern complex patterns from large datasets. Each layer can be conceptualized as a filter, progressively extracting more sophisticated features from the input data.

One-dimensional sensor signals are data streams that capture temporal changes in phenomena such as temperature, vibrations, or electrical activity. Deep learning proves particularly effective in analyzing these signals due to its ability to

automatically extract hidden patterns and features that may elude traditional analytical methods.

Deep learning can be applied to 1D sensor signal analysis in several ways:

- **Classification:** Categorizing signals based on their characteristics, such as distinguishing between speech, music, and noise in audio signals.
- **Anomaly detection:** Identifying unusual patterns that deviate from the norm, potentially indicating equipment failures or malfunctions.
- **Prediction:** Forecasting future signal values based on historical data, useful for preventive maintenance or resource optimization.
- **Regression:** Estimating continuous values from signal data, such as pressure or concentration levels.

1.2.13 Advantages of Deep Learning for 1D Sensor Signals

- **Automated feature extraction:** Deep learning eliminates the need for manual feature engineering, increasing efficiency.
- **Enhanced accuracy:** Deep learning models often outperform traditional methods in various tasks.
- **Versatility:** These models can be adapted to different types of 1D signals with minimal modifications.
- **Real-time processing:** Certain deep learning architectures are suitable for immediate analysis of sensor data.

Deep learning architectures

- **One-Dimensional Convolutional Neural Networks (1D CNNs):** Adapted from image-processing CNNs, these use filters that slide across time series data to extract local features and patterns.
- **Recurrent Neural Networks (RNNs):** These networks process data sequentially, maintaining information from previous time points to contextualize current data.
- **Autoencoders:** These networks compress and reconstruct input data, identifying key features in the process. They can be used for preprocessing or dimensionality reduction before further analysis.

The selection of a specific deep learning architecture and technique depends on the particular task and characteristics of the 1D signal data being analyzed.

1.3 RNN

A recurrent neural network (RNN) is a specialized neural network architecture designed to process sequential data by maintaining an internal memory. It employs recurrent connections to preserve information across time steps, allowing it to capture temporal dependencies in the data and make predictions or classifications based on the sequence's context. RNNs are widely applied in tasks such as natural language processing, speech recognition, and time series analysis. Given that much of the data collected from mobile sensors is time series in nature, RNNs are a preferred choice in one of our proposed implementation strategies for crime detection.

Figure 1.9 illustrates the structure of a recurrent neural network. The RNN comprises multiple hidden layers, each containing recurrent units. These units are interconnected in a loop, enabling the network to learn long-term dependencies in the data.

An RNN processes a sequence of input vectors and generates a sequence of output vectors. At each time step, the RNN:

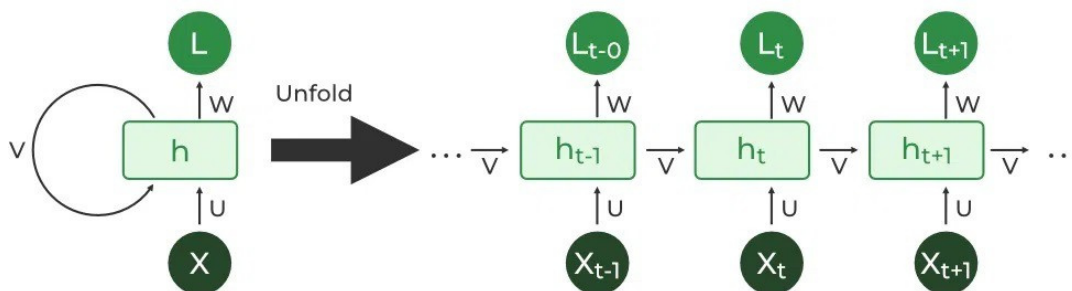


Fig. 1.9 : The structure of a Recurrent Neural Network (RNN), designed to process sequential data. RNNs excel at learning long-term dependencies, making them suitable for tasks like natural language processing, machine translation, and speech recognition.

1. Receives the input vector for the current time step.
2. Updates its hidden state based on the current input and previous hidden state.
3. Produces an output vector derived from the current hidden state.

This process is repeated for each time step in the input sequence. RNNs have diverse applications, including:

- Natural language processing: Text generation, language translation, and comprehensive question answering.

- Machine translation: Converting text between languages.
- Speech recognition: Transforming speech into text.
- Image captioning: Generating descriptive captions for images.
- Video analysis: Identifying objects and events in video content.

RNNs are powerful tools for sequential data processing, capable of learning long-term dependencies that make them well-suited for various tasks.

Table 1.1: Comparison of ANN, CNN, and RNN

	ANN	CNN	RNN
Basics	One of the simplest types of neural networks.	One of the most popular types of neural networks.	The most advanced and complex neural network
Structural Layout	Its simplicity comes from its feed forward nature – information flows in one direction only.	Its structure is based on multiple layers of nodes including one or more convolutional layers.	Information flows in different directions, which gives it its memory and self-learning features.
Data Type	Fed on tabular and text data.	Relies on image data.	Trained with sequence data.
Complexity	Simple in contrast with the other two models.	Considered more powerful than the other two.	Fewer features than CNN but powerful due to its self-learning & memory potential.
Commendable feature	Ability to work with incomplete knowledge and high fault tolerance.	Accuracy in recognizing images.	Memory and self-learning.
Feature type: spatial recognition	No	Yes	No

	ANN	CNN	RNN
Feature type: Recurrent connections	No	No	Yes
Main Drawback	Hardware dependence	Large training data required	Slow and complex training and gradient concerns.
Uses	Complex problem solving such as predictive analysis	Computer vision including image recognition	Natural language processing including sentiment analysis and speed recognition.

Table 1.1 compares the characteristics of ANN, CNN, and RNN architectures. RNNs can be classified into four types based on their input-output structure:

1. **One-to-One:** Functions similarly to a simple neural network, with a single input and output.
2. **One-to-Many:** Processes a single input to produce multiple outputs, exemplified by image captioning tasks.
3. **Many-to-One:** Handles multiple inputs to generate a single output, as seen in sentiment analysis applications.
4. **Many-to-Many:** Processes multiple inputs to produce multiple outputs, commonly used in machine translation tasks.

1.4 LSTM

LSTM (Long Short-Term Memory) is an advanced type of recurrent neural network (RNN) designed to learn long-term dependencies in data. It was developed to address the vanishing gradient problem that often occurs when training traditional RNNs. The vanishing gradient problem in RNNs refers to the phenomenon where the gradient of the loss function with respect to the network weights becomes extremely small or zero as it propagates backwards through time. This results in minimal or no updates to the weights of earlier layers, making it challenging for the network to learn long-term dependencies in the data. This issue arises from the repeated multiplication of the

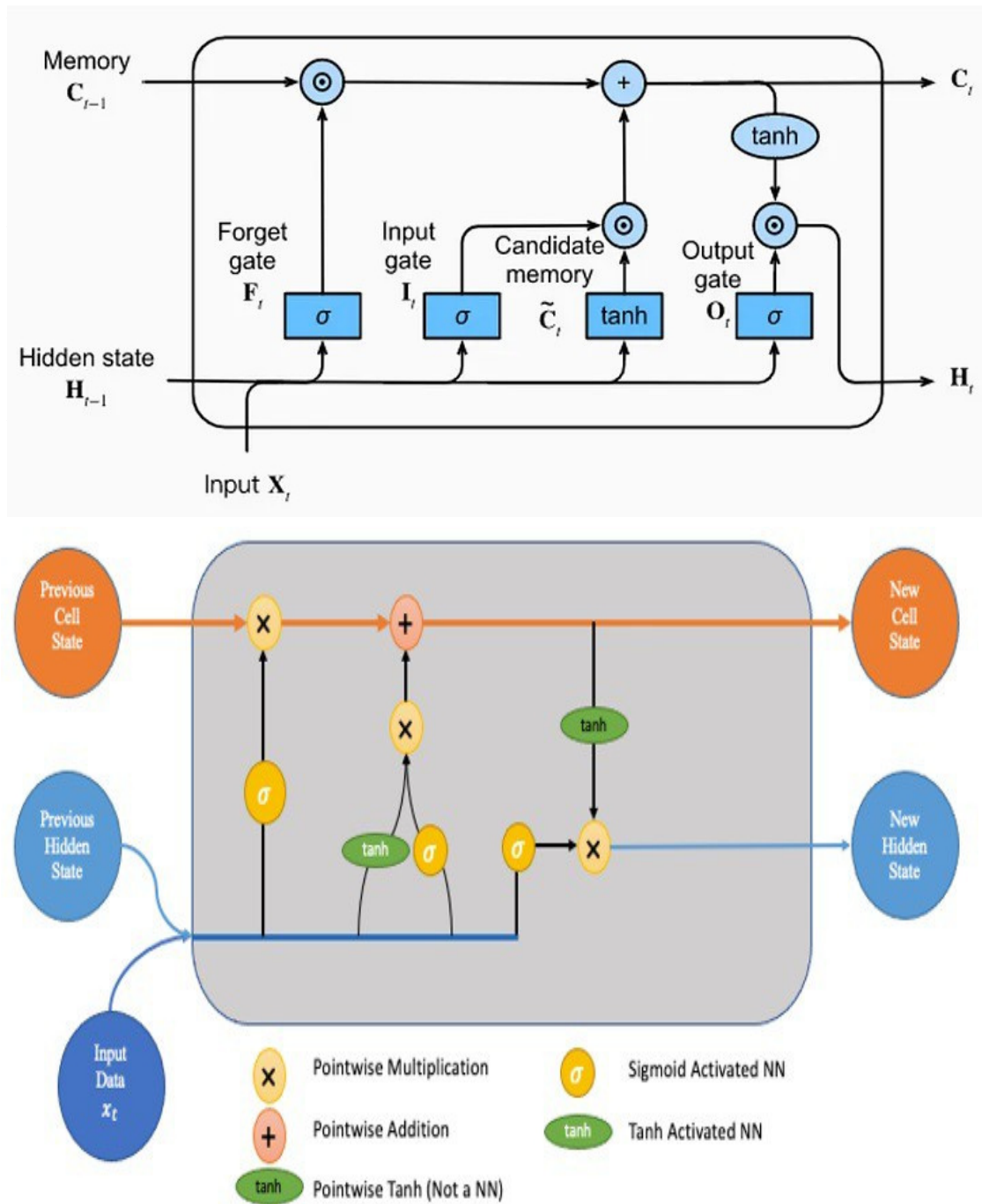


Fig. 1.10 : Long short-term memory (LSTM) network structure

Figure 1.10 illustrates the structure of an LSTM network. An LSTM cell comprises three main elements: the cell state, hidden state, and gates. The cell state stores long term information, while the hidden state retains short-term information. The gates control information flow within the cell.

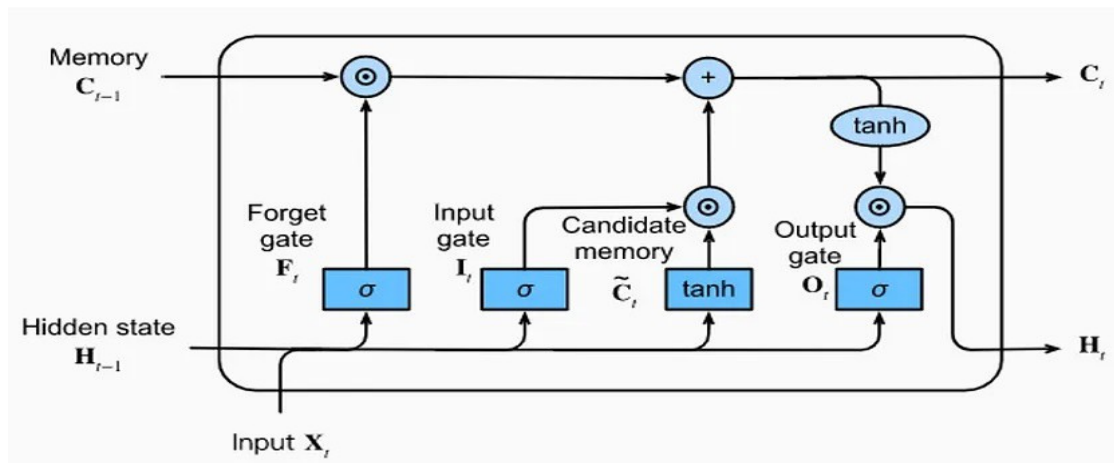


Fig. 1.11: LSTM network structure, designed to learn long-term dependencies in data through gating mechanisms that control information flow

The three types of gates in an LSTM cell are:

- Forget gate: Determines which information from the previous cell state should be discarded
- Input gate: Decides which new information should be added to the cell state
- Output gate: Selects which information from the cell state should be passed to the next hidden state

These gates regulate information flow through the LSTM cell. At each time step, input data is processed and the cell state is updated. The gates selectively allow information to be added, removed, or transmitted, ensuring relevant information is retained while unnecessary data is discarded.

Key mathematical operations in an LSTM cell include pointwise multiplication, addition, and the use of activation functions like tanh and sigmoid. These operations contribute to the LSTM's ability to learn long-term dependencies.

LSTMs are widely used in various domains, including natural language processing, time series prediction, and machine translation. In our thesis, we will input 1D sensor data to an LSTM network to achieve event classification.

Figure 1.11 shows a block diagram of an LSTM cell, consisting of four main components:

- Input gate: Controls information flow from the input vector and previous hidden state into the cell state

- Forget gate: Regulates information outflow from the cell state
- Cell state: The main memory unit, storing learned information about the input sequence up to the current time step
- Output gate: Manages information flow from the cell state to the output vector

The LSTM cell operates as follows:

1. Input gate processes the input vector and previous hidden state, determining their contribution to the cell state
2. Forget gate analyzes the previous hidden state to determine how much of the cell state to forget
3. Cell state is updated based on input gate, forget gate, and previous cell state
4. Output gate reads the cell state and determines the output amount

This process repeats for each time step in the input sequence.

LSTM networks excel at learning long-term dependencies by controlling information flow into and out of the cell state, allowing them to retain information for extended periods, even when not immediately relevant.

LSTMs are applied in various tasks, including:

- Natural language processing: Text generation, language translation, and comprehensive question answering.
- Machine translation: Converting text between languages
- Speech recognition: Transforming speech to text
- Image captioning: Generating descriptive image captions
- Video analysis: Identifying objects and events in video content

Table 1.2: Comparison of RNN, GRU, and LSTM

Parameters	RNNs	LSTMs	GRUs
Structure	Simple	More complex	Simpler than LSTM
Training	Can be difficult	Can be more difficult	Easier than LSTM
Performance	Good for simple tasks	Good for complex tasks	Can be intermediate between simple and complex tasks

Parameters	RNNs	LSTMs	GRUs
Hidden state	Single	Multiple (memory cell)	Single
Gates	None	Input, output, forget	Update, reset
Ablity to retain long-term dependencies	Limited	Strong	Intermediate between RNNs and LSTMs

LSTM networks are powerful tools for processing sequential data, capable of learning long-term dependencies that make them well-suited for diverse tasks.

Table 1.2 compares key differences between RNNs, LSTMs, and Gated Recurrent Units (GRUs).

1.5 Modified sub-space KNN (msK)

Along with LSTM for classification of the type of criminal activity, firstly such activity detection is important. It required binary classification, to detect normal or suspicious/ criminal activity. For this purpose of thesis work, we developed a novel subspace KNN method that can classify multiple suspicious activities. We have named this particular algorithm as, modified subspace KNN (msK) algorithm. The modified subspace KNN is a method that uses K neighborhood classification



Fig. 1.12 : Concept diagram of proposed suspicious activity detector using msK

with parallel implementation. In this msK algorithm, we create multiple KNN models for which data is sampled into subspaces, for example out of 1000 readings any five readings are randomly chosen and then compared with the current time point. If the number of points closer to normal activity are found to be more compared to suspicious activity then the current point is classified as normal. the main

modification to the sub-space KNN comes from the fact that we not only give the output class but also give the output probability that the current value belongs to that particular class (i.e. Normal or Suspicious). The diagram 1.12 illustrates the concept where data collected from a victim's mobile phone helps in detecting suspicious activity. The collected data is then fed into a modified subspace KNN algorithm, which aids in the binary detection process.

1.6 Need for the proposed work

There are at least 20 % raise in forensic criminal cases after 2021, after the COVID-19 outbreak. Most people started working from home and activities inside the house have raised a lot. Due to this multiple fights within the house has raised. There are some cases, where dead bodies were found inside closed doors, but the reason remains unknown. It could be the natural cause of death, such as, heart attack, brain hemorrhage, cardiac arrest, etc. or it could be suicide or even it could be murder. Investigation of such cases is very difficult for the policeman. The body postmortem report can reveal many ambiguities. But, for to be sure, investigators can make use of a device that is loaded with sensors (i.e. mobile phone).

Our approach in the proposed method that, will give a stepping stone for mobile phone-based digital forensics. There could be other cases other than murder, such as robbery, rape, accidents, etc. where the digital forensics using mobile phone can be very useful.

Daily activities such as sleeping, going to the park, jogging, and traveling are common for everyone. However, unforeseen and unpleasant circumstances can arise during these activities. People may fall victim to various criminal acts, such as robbery, kidnapping, assault, murder, extortion, and theft while commuting to work or engaging in routine tasks. These crimes inflict significant stress on the victims, causing changes in their body posture, heart rate, oxygen levels, and other vital signs. If such information were readily accessible to law enforcement agencies, they would be able to make more informed decisions. However, a major challenge currently lies in the timely collection and transmission of this information to the appropriate authorities, hindering their ability to respond effectively. Therefore, it is essential to establish a mechanism for collecting and transferring this critical information

promptly. Once data is collected, we can then apply our msK, LSTM and novel IF Densenet-138 to figure out the type of crime that might have happened.

1.6.1 Importance of suspicious activity detection using mobile sensor data

In today's world, mobile phones have seamlessly integrated into our lives, boasting nearly 8 billion users globally, with about 6.6 billion being smartphone users. This extensive adoption of mobile sensors highlights the need to optimize this technology's potential. Unfortunately, the prevalence of criminal activities is on the rise, with India alone reporting over 6.6 million cases in 2020. This alarming statistic underlines the urgent requirement for advanced technologies to counteract these crimes. A striking example is the daily occurrence of approximately 80–82 murders in India, where the victims can't provide firsthand accounts, complicating evidence collection by law enforcement.

As individuals frequently inhabit public spaces like malls, parks, and others, criminal incidents have become commonplace, spanning robbery, assault, and even murder. Criminal behavior often alters body posture and vitals over time. Tracking and recording vital parameters such as heartbeat rates, oxygen levels, and body posture could significantly aid law enforcement in pinpointing attackers and enhancing public safety. Addressing real-time crime reporting and swift response challenges has become crucial due to the escalating crime rates. In this context, the mobile and Internet of Things (IoT) devices, emerges as a promising solution. By creating an efficient IoT system, individuals can promptly capture and report crimes in real-time. Simultaneously, law enforcement can receive timely alerts through a mobile application, facilitating swift intervention. IoT mobile systems aim to foster connectivity between humans and sensors, reducing the need for extensive human involvement. The primary goal of this proposed model is to develop a mobile application that enhances the bond between the public and law enforcement, ultimately contributing to society's well-being.

Approximately 750,000 police cases are annually dismissed in India due to a lack of evidence, leading to unsolved cases and low conviction rates. The Indian criminal justice system's inadequacies stem partly from insufficient evidence collection and preservation. Factors like underfunding, understaffing, and lack of forensic science

and technology training in law enforcement agencies hinder proper evidence handling, impacting case resolution. Mobile device forensics, a subset of digital forensics, offers a solution. It involves recovering digital evidence from mobile devices in a forensically sound manner. Mobile forensics consists of three stages: seizure, acquisition, and examination/analysis, all aiming to recover and interpret digital evidence. This process plays a pivotal role in using mobile phone data as evidence in legal proceedings, adhering to data privacy laws and constitutional requirements.

Deep learning, a subfield of machine learning inspired by neural networks in the human brain, holds immense potential in crime investigation using mobile data. Its ability to analyze vast and intricate datasets, including call logs, text messages, and social media activity, stands out. Deep learning uncovers hidden patterns and connections in data that human investigators might miss, making it invaluable for tracking suspects and reconstructing events. It's also adapts to analyze images, videos, and text messages for crime detection and response. Among the deep learning techniques, DenseNet, a convolutional neural network architecture, outperforms traditional CNNs by reusing features through "dense blocks," addressing challenges like vanishing gradients and optimizing learning processes.

1.7 Objectives

1. To develop a platform capable of efficiently collecting data from multiple sensors on mobile devices.
2. To analyze the performance of the proposed deep learning algorithms on the collected sensor data. The focus will be on developing and optimizing a suitable deep learning model for classification, enabling accurate crime detection.
3. To develop a multi-class deep learning model, the study involves collecting various types of simulated forensic case data and optimizing the model. This process aims to provide valuable insights for crime scene investigation and analysis.
4. To evaluate the effectiveness and efficiency of the developed platform and deep learning model in real-time scenarios. Additionally, the platform will be

tested against crime simulations with various scenarios involving trained actors to ensure the robustness of the proposed system.

1.8 Research Gap

While the objectives of this study are ambitious and comprehensive, there are a few notable gaps in the existing literature that this research aims to address. Firstly, there is a lack of a comprehensive platform that can efficiently collect data from multiple sensors on mobile devices. Existing solutions are either limited in scope or not optimized for real time data collection, making them unsuitable for forensic applications. Secondly, while deep learning algorithms have shown promise in various domains, their effectiveness in crime detection and scene analysis is not well-documented. The proposed deep learning model aims to bridge this gap by providing a robust and accurate solution tailored specifically for forensic applications. Thirdly, while there are some studies on multi-class deep learning models, they are mostly focused on specific applications and lack a comprehensive evaluation framework. This study aims to fill this gap by developing a multi-class deep learning model that can be applied across various forensic scenarios. Finally, while there are some studies that have evaluated the effectiveness of deep learning models in forensic applications, they are mostly limited to simulated data. This study aims to address this gap by evaluating the developed platform and deep learning model in real-world scenarios, providing valuable insights into their effectiveness and efficiency.

1.9 Organisation of the thesis

Chapter 1: The introduction chapter delves into the utilization of sensor data pattern analysis for post-crime detection and the tracking of criminals. It elucidates the project's necessity, delineates the aims and objectives of the thesis, and provides an overview of the deep learning models employed in the present thesis work.

Chapter 2: Literature Review offers an encompassing review of the existing literature pertinent to sensor data pattern analysis and crime detection.

Chapter 3: Methodology chapter explore upon the methods adopted for the utilization of sensor data pattern analysis in criminal tracking. It encompasses the various methods employed during the thesis implementation, including mSK, LSTM, and others.

Chapter 4: Results showcases all the outcomes achieved during the course of the thesis work.

Chapter 5: Discussions delves deep into an intricate analysis of the potential reasons underpinning the acquired results. It further considers the critical factors for conducting pattern analysis and applying AI algorithms, highlighting essential facets during the analysis procedure.

Chapter 6: Conclusions and Future Directions concludes the thesis by emphasizing the challenges and prospects linked with employing sensor data pattern analysis for post-crime detection and criminal tracking. It offers recommendations for forthcoming research endeavors in this domain.