Final Year Project Report

TRAFFIC ACCIDENT DETECTION WITH COMPUTER VISION USING AUTONOMOUS UAV

Submitted by:

Syed Yasir-Ul-Haq (Group Leader)	**(19F-CS-16)**
Muhammad Faizan	**(19F-CS-07)**
Abdullah Saqib	**(19F-CS-22)**
Suresh Kumar	**(19F-CS-49)**

SUPERVISED BY:

ENGR. MOTIA RANI
ASSISTANT PROFESSOR OF COMPUTER SYSTEM ENGINEERING
DEPARTMENT, DUET

Batch 2019-Fall
Department of Computer System Engineering
Dawood University of Engineering and Technology

CERTIFICATE

This is certified that the work presented in this project report "**TRAFFIC ACCIDENT DETECTION WITH COMPUTER VISION USING AUTONOMOUS UAV**" is entirely written by the following students under the supervision of **ENGR. MOTIA RANI**. This project is found complete and submitted to partially fulfill the requirement for a Bachelor of Computer System Engineering degree.

Submitted by:

Syed Yasir-Ul-Haq (Group Leader)	**(19F-CS-16)**
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Abdullah Saqib	**(19F-CS-22)**
Suresh	**(19F-CS-49)**

SUPERVISOR
ENG. MOTIA RANI
Dept. Computer System Engineering

EXTERNAL EXAMINER

CHAIRPERSON
Dr. Saleem Ahmed
Dept. Computer System Engineering

DEPARTMENT OF COMPUTER SYSTEM ENGINEERING DAWOOD UNIVERSITY OF ENGINEERING AND TECHNOLOGY, KARACHI

ACKNOWLEDGEMENT

To begin, we extend our heartfelt gratitude to Allah, whose strength and enabling presence allowed us to accomplish our thesis. Without His divine assistance, this achievement would have remained beyond our reach. Numerous individuals deserve our acknowledgment for their invaluable contributions to the successful culmination of this dissertation.

Our deepest appreciation and thanks go to our primary supervisor, **Engr. Motia Rani**, whose unwavering support played a pivotal role in guiding us through the completion of our work. Her assistance and guidance will forever be cherished.

We take great pleasure in expressing our gratitude to **Dr. Saleem Ahmed, Chairperson of the Department of Computer System Engineering at DUET**.

We also wish to express our gratitude to our esteemed seniors who provided thorough assistance throughout this project.

Lastly, our sincere thanks extend to all the faculty members and friends whose valuable advice and support played a crucial role in the successful realization of this project.

DEDICATION

This dissertation is devoted to **Our Dear Parents**, whose boundless affection, backing, and inspiration were indispensable. Without their prayers and motivation, this accomplishment would have remained unattainable. Their unwavering belief in our potential fueled our determination to succeed.

ABSTRACT

Accidents on roadways pose a significant threat to public safety and often require prompt intervention for effective response and mitigation. This thesis presents an innovative approach to accident detection using an autonomous drone equipped with computer vision technology. The goal is to leverage the capabilities of computer vision algorithms and unmanned aerial vehicles (UAVs) to enhance safety and response efficiency in accident-prone areas. By autonomously patrolling road networks, the drone can quickly detect and report accidents, enabling timely emergency response and reducing potential hazards for commuters. This research explores the development, implementation, and evaluation of an accident detection system based on computer vision techniques, drone navigation, and communication protocols. The results demonstrate the potential of this technology to revolutionize accident detection and response systems, ultimately leading to safer roadways and improved emergency services.

Accurate and prompt accident detection holds immense potential for improving road safety and emergency response systems. This thesis presents an innovative approach to real-time accident detection using computer vision techniques. The proposed system utilizes a dataset of video frame images, categorized into "Accident" and "No Accident" folders, to train a Convolutional Neural Network (CNN) model. The methodology involves data preprocessing, model architecture design, and rigorous training. Key performance metrics including accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC-ROC) are systematically evaluated to measure the model's efficiency in binary image classification. The system's robustness to varying ambient conditions, such as sunlight, snow, and night, is assessed, highlighting its adaptability across scenarios. Additionally, communication reliability is gauged by analyzing the accuracy and timeliness of SMS alerts. The achieved results demonstrate a promising detection accuracy of 86%, along with notable precision and recall scores. Furthermore, the system exhibits favorable performance in varying ambient conditions. This thesis contributes to the development of an effective real-time accident detection system with potential applications in road safety and emergency response.

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INTRODUCTION

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1.1 INTRODUCTION:

Traffic accidents are one of the biggest causes of deaths and injuries globally. According to the World Health Organization, more than 1.3 million people die each year because of road traffic collisions, and up to 50 million more are wounded. Rapid and precise identification of traffic accidents is vital for saving lives and decreasing the effect of traffic congestion. However, typical means of accident detection, such as human reporting, sensors, or cameras, have limits in terms of coverage, reliability, and expense.

However, traditional methods of accident detection, such as manual reporting by witnesses or drivers, sensors embedded in the road infrastructure, or cameras installed along the road network, have several limitations that hinder their performance and applicability. For instance, manual reporting can be delayed, inaccurate, or incomplete, depending on the availability and reliability of the reporters. Sensors can be costly to install and maintain and can cover only a limited area of the road network. Cameras can be affected by weather conditions, occlusions, or vandalism, and can generate a large amount of data that requires intensive processing and storage.

In this study, we present a unique technique for traffic accident detection combining computer vision and autonomous unmanned aerial vehicles (UAVs). We intend to design a system that can autonomously deploy UAVs to monitor traffic conditions and identify accidents using image processing and machine learning methods. The UAVs may give a bird's eye perspective of the traffic scene and send real-time photos and videos to a central server for analysis and verification. The technology may also notify the necessary authorities and give vital information for emergency response and traffic management.

This project will contribute to the field of intelligent transportation systems by delivering a unique approach for traffic accident detection that may overcome the limits of existing technologies. It will also have potential uses in other fields that need aerial surveillance and picture processing, such as disaster management, security, agriculture, or wildlife protection.

1.2 PROJECT BACKGROUND AND HISTORY:

Traffic accidents on highways represent a substantial danger to public safety and result in the loss of countless lives each year. The fast and efficient reaction to such catastrophes is crucial in reducing their impact. However, traditional techniques of accident detection and reaction sometimes prove to be sluggish and inaccurate, particularly in the setting of highways. This project intends to build an intelligent and efficient accident detection and response system particularly intended for highways. By utilizing sophisticated technology and creative methodologies, the proposed system intends to greatly increase the speed and reliability of accident detection and reaction, hence boosting overall traffic safety on motorways.

Motorways are high-speed road networks where accidents can have serious effects. Rapid detection and response to incidents are vital for reducing their impact. Traditional methods of accident detection and response can suffer from delays and mistakes, leading to greater risks and protracted interruptions. This research presents an intelligent and efficient accident detection and response system to solve these constraints.

This project intends to solve the limits of existing accident detection and response systems on highways by establishing an intelligent and efficient system. Through the integration of sophisticated technologies and data analysis methodologies, the suggested system has the potential to dramatically increase the speed and reliability of accident detection and reaction. By limiting the effect of accidents, the system can help to improve the safety and efficiency of highway transit, eventually saving lives, and lowering economic losses connected with traffic accidents.

1.3 PROBLEM STATEMENT:

To make the UAV autonomous so that could travel to the stations. The purpose of this project is to construct an autonomous UAV system capable of navigating and going to a predetermined station without human involvement. The UAV should be able to plot its path, avoid obstructions, and make real-time decisions to guarantee a safe and efficient travel. The system will include computer vision algorithms to sense the surroundings and make intelligent judgments based on the observed items and barriers. The UAV's autonomy will be realized by the integration of modern navigation systems, obstacle avoidance algorithms, and strong communication protocols. The project will focus on establishing an end-to-end system that incorporates mission planning, obstacle detection and avoidance, as well as communication and control interfaces. This autonomous UAV system can have several applications, including delivering items, conducting surveillance flights, or aiding in search and rescue operations.

To detect car accidents on motorway using computer vision during regular patrolling. The purpose of this project is to use computer vision methods for the real-time identification of automobile accidents on the freeway during frequent patrols. The technology will deploy UAVs outfitted with cameras to record live video footage of the road. The collected video frames will be analyzed using computer vision algorithms to detect and identify probable automobile accidents or events. The algorithms will examine the video stream to discover patterns connected with accidents, such as rapid changes in vehicle velocity, crashes, or strange behavior. Once an accident is spotted, the system will provide alerts or notifications to the proper authorities for rapid reaction and help. The project will require building and implementing an efficient and accurate computer vision pipeline that comprises object detection, tracking, and event identification algorithms. The system should be capable of functioning in real-time, manage various lighting and weather conditions, and achieve a high degree of accuracy in accident detection to decrease false alarms and enhance emergency response on the road.

1.4 PROJECT OBJECTIVES:

1. **Creating a UAV that could fly autonomously.**

   The major purpose of this project is to design and construct an autonomous Unmanned Aerial Vehicle (UAV) capable of executing flight operations without human assistance. The UAV should be equipped with advanced sensors, navigation systems, and control algorithms to enable autonomous flight, including takeoff, waypoint navigation, and landing. The autonomous capabilities will boost the efficiency and safety of UAV operations, enabling for diverse applications such as airborne surveillance, package delivery, or search and rescue missions.

2. **Creating a UAV that could auto hover and land.**

   The main emphasis of this project is to add sophisticated control algorithms and sensing systems to enable the UAV to attain auto hover and accurate landing capabilities. The auto hover capability will allow the UAV to retain a steady position in the air, even in the face of external disturbances, while the precision landing capabilities will enable the UAV to land securely and correctly on predefined landing places. These capabilities are critical for enabling dependable and controlled UAV operations, especially in situations where manual control may be problematic or unfeasible.

3. **Creating a reporting system that reports the location of incident to the ground station**.

   To increase situational awareness and allow quick reaction, the project will include creating and deploying a reporting system. This system will receive and handle information from the UAV, especially the location data of identified events or mishaps. It will leverage communication protocols and link with a ground station or control center to communicate incident location data. This reporting system will support effective emergency response and enable authorities to promptly analyze and deploy relevant resources to the event area.

4. **Creating a computer vision program that could detect the accident and report it to reporting system.**

   Another key part of the project is to construct a computer vision algorithm capable of identifying accidents or events from the UAV's video feed. The application will apply modern image processing and machine learning techniques to examine video frames in real-time, recognizing patterns linked with accidents, such as collisions, rapid changes in velocity, or the presence of obstructions. Upon identification, the application will create warnings or notifications, interacting with the reporting system discussed before, enabling fast incident reporting to the ground station. The computer vision program's accuracy and efficiency in spotting accidents will lead to enhanced safety and reaction time on the highways.

1.5 SCOPE OF THE PROJECT:

The scope of this project titled "Traffic Accident Detection using Computer Vision and Autonomous UAV" is to design and develop a comprehensive system that combines an autonomous UAV with advanced computer vision techniques for real-time traffic accident detection and alerting. The autonomous UAV will be equipped with essential functionalities such as auto-hover, auto-landing, and waypoint navigation, which will enable it to navigate efficiently through predefined paths and accident-prone areas. For the computer vision aspect, state-of-the-art algorithms will be implemented to process live video feed captured by the UAV's onboard camera. This will involve training and fine-tuning a deep learning model using a diverse dataset of traffic accident images and videos, allowing the system to accurately detect and classify various types of incidents, including collisions, vehicle rollovers, and pedestrian accidents.

1.6 SIGNIFICANCE OF THE PROJECT:

This project holds significant importance in several domains and has the potential to make a substantial impact on road safety and emergency response. The significance of the project is as follows:

- **Improved road safety**:
  Combining computer vision and autonomous UAV technology, the system can efficiently monitor roads and identify traffic accidents in real time. This feature reduces response time from emergency services, reduces the likelihood of secondary accidents, and provides timely assistance to accident victims.

- **Accurate auto-detection:**
  Traditional incident detection methods are often based on human reporting, which can introduce delays and inaccuracies. Computer vision-based systems can autonomously detect and classify accidents with high accuracy, eliminating the need for human intervention and speeding up response times.

- **Faster response time:**
  Implementation of this project has the potential to significantly reduce response times for emergency services. Notifying ground stations of incidents in a timely manner enables first responders to be dispatched more efficiently, potentially saving lives and reducing the severity of injuries.

- **Real-time monitoring:**
  Integration of live video feeds from UAVs enables real-time road condition monitoring. This capability is beneficial for traffic management, providing valuable insights for authorities to manage congestion and take preventative measures to prevent accidents.

- **Cost effective solution:**
  Compared to traditional incident detection systems that require the installation of various sensors and infrastructure, the proposed system offers a more cost-effective solution. Deploying autonomous UAVs with computer vision technology is a more versatile and economical approach.

- **Versatility and scalability:**
  The developed system can adapt to different environments such as urban and rural areas, highways and intersections. In addition, it can be extended to cover larger areas or integrated into existing traffic management systems for wider implementation.

- **Research contributions:**
  Integrating computer vision technology into his UAV technology for this project will contribute to the advancement of computer vision research for autonomous systems and accident detection. It provides valuable insight into the practical application of these technologies for the benefit of society.

- **Public Safety Awareness:**
  The introduction of advanced accident detection systems will increase public awareness of the potential of state-of-the-art technology for road safety and accident avoidance. This project has the potential to stimulate discussion about the use of technology to improve road safety.

CHAPTER – 02
LITERATURE REVIEW

CHAPTER – 02 LITERATURE REVIEW

2.1 ACCIDENT DETECTION SYSTEMS:

There are several current accident detection systems that are being used or researched today. Here are some examples:

1. In-Vehicle Sensors: Many modern vehicles are equipped with sensors such as accelerometers, gyroscopes, and collision detection systems. These sensors can detect sudden changes in acceleration, deceleration, or impact and trigger an alert or emergency response, such as automatically deploying airbags or activating emergency services.

2. Connected Vehicle Technology: Connected vehicle technology allows vehicles to communicate with each other and with infrastructure, such as traffic lights and road signs. Through this communication, vehicles can exchange information about their position, speed, and other relevant data. If an accident occurs, this information can be shared with nearby vehicles and emergency services, enabling a faster response.

3. Smartphone Applications: Various smartphone applications use the sensors and GPS capabilities of mobile devices to detect accidents. These apps can analyze data such as sudden changes in velocity or a rapid decrease in battery level (indicating a potential impact) to determine if an accident has occurred. They can then send notifications or alerts to emergency contacts or emergency services.

4. CCTV and Traffic Surveillance Systems: Closed-circuit television (CCTV) cameras and traffic surveillance systems are widely used for monitoring roadways. These systems can employ computer vision algorithms to detect abnormal events or patterns, such as collisions or sudden stops. Once an accident is detected, alerts can be sent to the appropriate authorities for immediate response.

5. Machine Learning and Artificial Intelligence: Machine learning and artificial intelligence (AI) techniques are being used to develop sophisticated accident detection systems. These systems can analyze large amounts of data from various sources, such as traffic cameras, sensors, and social media feeds, to detect patterns indicative of accidents. They can also learn from historical accident data to improve accuracy and prediction capabilities.

6. Drone-based Surveillance: Drones equipped with cameras and sensors can be deployed to monitor roadways and detect accidents. Computer vision algorithms can analyze the drone's video feed in real-time to identify signs of accidents, such as damaged vehicles or injured individuals. The drone can then relay this information to emergency services or act as a first responder.

It is important to note that the effectiveness and availability of these systems may vary depending on the location and infrastructure. Additionally, ongoing research and advancements in technology continue to improve accident detection systems, making them more accurate and efficient.

2.2 COMPUTER VISION IN ACCIDENT DETECTION

Computer vision has proven to be a valuable tool in accident detection and prevention, revolutionizing the way we approach safety on roads and in various industries. By leveraging advanced image processing techniques and machine learning algorithms, computer vision systems can analyze visual data from cameras and sensors to identify potential accidents or hazardous situations in real-time. This technology has the potential to significantly reduce the number of accidents, injuries, and fatalities by enabling proactive intervention and timely response.
Accident detection using computer vision involves several key components and processes. Let's delve into them in detail:

- **Data Acquisition:** The first step is to collect relevant visual data using cameras or other imaging devices. These cameras can be installed on vehicles, roadside infrastructure, or in stationary locations to provide comprehensive coverage of the environment. Additionally, other sensors such as lidar and radar can be employed to enhance the accuracy of the system.

- **Image Preprocessing:** Once the visual data is acquired, it needs to be preprocessed to enhance the quality and extract useful information. This involves tasks such as image stabilization, noise reduction, image enhancement, and calibration. Preprocessing ensures that the subsequent analysis is performed on reliable and accurate data.

- **Object Detection:** The next step is to identify and locate objects of interest in the captured images or video streams. Object detection algorithms, such as the popular ones like Faster R-CNN, YOLO, or SSD, are used to detect and classify various objects, including vehicles, pedestrians, cyclists, and obstacles. These algorithms leverage deep learning techniques to analyze visual features and make predictions about the presence and location of objects in real-time.

- **Trajectory Prediction:** Once the objects are detected, trajectory prediction algorithms can be employed to estimate the future paths and movements of these objects. By analyzing their current positions, velocities, and acceleration patterns, these algorithms can provide insights into potential collision risks or dangerous situations. This information is crucial for accident detection and prevention systems to take timely action.

- **Anomaly Detection:** Apart from tracking and predicting trajectories, computer vision systems can also identify anomalies in the environment or behavior of objects. This can include sudden changes in the speed, direction, or behavior of vehicles, or the presence of unexpected obstacles on the road. Anomaly detection algorithms, often based on machine learning techniques, can learn from historical data to identify abnormal patterns and trigger appropriate responses.

- **Decision-Making and Intervention:** Once an accident or potential hazardous situation is detected, the computer vision system can initiate appropriate actions or alerts. This can involve sending real-time notifications to drivers, triggering automatic braking systems, or notifying emergency services. Advanced systems can also communicate with traffic infrastructure, such as traffic lights, to optimize traffic flow and prevent accidents.

- **Data Analysis and Improvement:** The data collected by accident detection systems can be analyzed to gain insights into the causes and patterns of accidents. This analysis can help identify high-risk areas, common accident scenarios, or driver behaviors leading to accidents.

These insights can be used to improve road design, traffic regulations, driver training, and the overall safety ecosystem.

Computer vision in accident detection has been applied in various domains, including autonomous vehicles, transportation infrastructure, industrial safety, and surveillance systems. The technology has the potential to significantly reduce human errors, improve response times, and enhance overall safety on roads and in workplaces.
However, it's important to acknowledge that computer vision systems are not infallible, and there are certain challenges and limitations associated with their implementation. Factors such as adverse weather conditions, occlusions, varying lighting conditions, and rapidly changing environments can affect the accuracy and reliability of accident detection systems. Continuous research and development efforts are essential to address these challenges and ensure the robustness of computer vision-based accident detection solutions.
In conclusion, computer vision has emerged as a powerful tool in accident detection, leveraging image processing and machine learning algorithms.

2.3 AUTONOMOUS DRONE IN SURVEILLANCE

Autonomous drones have become increasingly prevalent in surveillance applications, offering a range of capabilities that enhance security, monitoring, and data collection. These unmanned aerial vehicles (UAVs) equipped with advanced sensors, cameras, and autonomous flight capabilities have transformed the way surveillance operations are conducted. They provide a versatile and efficient means of gathering visual information, conducting aerial reconnaissance, and monitoring areas that are difficult to access by conventional means. Let's explore the detailed aspects of using autonomous drones in surveillance:

1. **Aerial Monitoring:** Autonomous drones enable aerial monitoring of vast areas, providing a bird's-eye view of the surroundings. With their ability to fly at varying altitudes and capture high-resolution images and video, they offer comprehensive surveillance coverage. This makes them particularly useful for large-scale applications such as border control, critical infrastructure protection, crowd management, and event security.

2. **Real-Time Video and Image Capture:** Drones equipped with cameras can capture real-time video footage and images from different perspectives. These visuals can be streamed directly to a control center, enabling operators to monitor events and situations in real-time. The high-resolution imagery allows for detailed analysis and identification of objects, individuals, or potential threats.

3. **Rapid Deployment and Mobility:** Autonomous drones can be rapidly deployed to areas of interest, reducing response times and providing a quick aerial presence. Their mobility and agility allow them to navigate challenging terrain, reach remote locations, and monitor dynamic situations such as traffic incidents, natural disasters, or search and rescue operations. They offer a flexible surveillance solution that can be easily repositioned as needed.

4. **Autonomous Flight and Navigation:** Modern drones are equipped with advanced flight control systems, including GPS navigation, obstacle avoidance sensors, and intelligent flight planning algorithms. These features enable autonomous operation, allowing drones to follow pre-defined flight paths, conduct area patrols, or autonomously track moving targets. Autonomy reduces the need for manual piloting, freeing up operators to focus on surveillance analysis and decision-making.

5. **Sensor Integration:** Drones can be equipped with various sensors beyond cameras to enhance surveillance capabilities. Thermal cameras can detect heat signatures, enabling nighttime surveillance, identifying hidden individuals, or identifying potential fire hazards. Gas or chemical sensors can detect and monitor air quality, alerting operators to potential hazardous substances. LIDAR sensors enable 3D mapping and object recognition, enhancing situational awareness.

6. **Data Analytics and Automation:** The data collected by autonomous drones can be processed and analyzed using advanced analytics techniques. Computer vision algorithms can be applied to detect and track objects of interest, identify abnormal behavior or potential threats, and generate actionable insights. Automated processes can be implemented to filter, classify, and prioritize surveillance data, reducing the burden on operators and facilitating efficient decision-making.

7. **Integration with Security Systems**: Autonomous drones can be integrated with existing security systems to enhance their effectiveness. They can be synchronized with ground-based cameras, access control systems, or alarm systems, providing a comprehensive surveillance network. When integrated with artificial intelligence (AI) systems, drones can respond to specific triggers, such as unauthorized access or perimeter breaches, autonomously investigating and providing real-time situational awareness.

8. **Safety and Privacy Considerations:** The use of autonomous drones in surveillance raises important considerations regarding safety and privacy. Safety measures should be in place to prevent collisions with other aircraft, people, or structures. Privacy guidelines and legal frameworks should be followed to ensure that surveillance operations respect individual privacy rights and adhere to applicable regulations.

Autonomous drones have the potential to revolutionize surveillance operations by providing a cost-effective, flexible, and efficient solution. They enable real-time monitoring, rapid response, and enhanced situational awareness in a variety of sectors, including law enforcement, critical infrastructure protection, disaster management, and public safety. Ongoing advancements in drone technology, sensor capabilities, and data analytics will continue to drive innovation in this.

2.4 EXISTING APPROACHES AND TECHNOLOGIES

In this section, we delve into the existing landscape of approaches and technologies pertaining to accident detection and prevention systems. The field has witnessed substantial advancements driven by the integration of computer vision, machine learning, and emerging technologies. Traditional methods involving manual surveillance and reporting have given way to sophisticated automated solutions that capitalize on real-time data analysis and intelligent algorithms.

2.4.1 COMPUTER VISION-BASED APPROACHES

Computer vision has emerged as a cornerstone in accident detection systems. Techniques such as object detection, image classification, and semantic segmentation have been pivotal in accurately identifying and classifying accidents from video streams and image data. These methods leverage deep learning architectures, like Convolutional Neural Networks (CNNs), to extract intricate features from visual data. This enables systems to discern between accident-related elements and normal traffic patterns, enhancing accuracy and reducing false positives.

2.4.2 SENSOR-BASED SOLUTIONS

Sensor-based technologies have also played a significant role in accident detection. These encompass a spectrum of sensors, such as accelerometers, gyroscopes, and LiDAR (Light Detection and Ranging), which capture real-time data related to vehicle dynamics, position, and environment. These data sources contribute to the development of predictive models and anomaly detection algorithms, enabling systems to identify unusual patterns and trigger alerts.

2.4.3 INTEGRATION OF IOT AND CONNECTIVITY

The advent of the Internet of Things (IoT) has revolutionized accident detection by enabling seamless connectivity among vehicles, infrastructure, and central monitoring systems. Connected vehicles can share real-time information about road conditions, vehicle speeds, and potential collisions, facilitating anticipatory measures. IoT-driven solutions enhance the scope of accident prevention by enabling timely warnings to drivers and traffic management authorities.

2.4.4 UNMANNED AERIAL VEHICLES (UAVS)

Unmanned Aerial Vehicles (UAVs), or drones, have emerged as a promising tool in accident detection and response. These aerial platforms offer unique vantage points, capturing visual data from perspectives that ground-based systems may miss. Integrating drones with advanced computer vision techniques allows for rapid deployment during emergencies, enabling swift and accurate assessment of accident scenes.

2.4.5 DATA FUSION AND PREDICTIVE ANALYTICS

Modern accident detection systems leverage the power of data fusion and predictive analytics. By amalgamating data from various sources, such as traffic cameras, GPS, and weather sensors, these systems can anticipate potential accidents based on historical patterns and real-time events. Predictive analytics enable early warning systems, optimizing traffic flow and preemptively reducing the likelihood of accidents.

2.4.6 CHALLENGES AND FUTURE DIRECTIONS

While these technologies offer promising solutions, challenges remain, including data privacy concerns, real-time processing constraints, and adaptability across diverse environmental conditions. Future research will likely focus on refining existing methodologies, integrating UAVs with real-time data streams, and harnessing the potential of emerging technologies such as 5G communication and edge computing.

In summary, the literature review highlights the evolution of accident detection technologies, emphasizing the significance of computer vision, sensor fusion, connectivity, and UAVs. These advancements collectively shape the landscape of proactive accident detection and pave the way for safer and more efficient roadways.

CHAPTER – 03
METHODOLOGY

CHAPTER – 03 METHODOLOGY

3.1 SYSTEM ARCHITECTURE

3.1.1 HARDWARE ARCHITECTURE:

1. Autonomous UAVs: Equipped with high-resolution cameras, GPS modules, and wireless communication capabilities, the UAVs capture images and videos of motorways. The UAVs are programmed to autonomously navigate the motorways, following predefined flight paths or dynamically adjusting their routes based on traffic conditions.

2. Central Processing Unit: The central processing unit serves as the core hardware component where the captured imagery is received and processed in real-time. It may consist of a powerful computer or server equipped with sufficient computational resources and storage capacity.

3. Storage Systems: Robust data storage systems, such as cloud-based storage or distributed file systems, are employed to store the captured images, videos, and relevant metadata. These storage systems provide scalability, reliability, and efficient retrieval of the stored data.

4. Communication Infrastructure: The system utilizes communication infrastructure, such as wireless networks or cellular networks, to transmit the captured imagery and accident information in real-time. It ensures seamless communication between the UAVs, central processing unit, and emergency response center.

3.1.2 SOFTWARE ARCHITECTURE:

1. Image and Video Processing Algorithms: Advanced computer vision algorithms are implemented as software components to analyze the captured imagery. These algorithms include pre-processing techniques for noise reduction and image enhancement, object detection algorithms for accident detection, and additional algorithms for accident classification, tracking, and localization.

2. Machine Learning Models: Machine learning models, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), are utilized to enhance the accuracy and performance of accident detection algorithms. These models are trained on historical accident data and regularly updated to adapt to evolving traffic patterns.

3. Data Storage and Management Software: Software components are employed to handle data storage, indexing, metadata management, and data retrieval tasks. These components ensure efficient storage and retrieval of captured imagery and relevant accident information.

4. Communication Protocols: Software protocols, such as HTTP or MQTT, are utilized for secure and efficient transmission of accident information between the UAVs, central processing unit, and emergency response center. These protocols enable real-time reporting of detected accidents and facilitate prompt response by emergency services.

5. User Interface Software: User interface components, which can be web-based or mobile-based, provide visualization of detected accidents, accident locations on maps, real-time alerts, and notifications. These components facilitate interaction and decision-making for emergency responders and system operators.

6. Security and Privacy Software: Software components are implemented to ensure privacy and security of the captured data. Anonymization techniques, secure communication protocols, access control mechanisms, and encryption algorithms are employed to protect sensitive information and prevent unauthorized access or tampering.

7. System Evaluation and Performance Metrics Software: Software components are utilized to evaluate the system's performance and measure accuracy metrics, such as precision, recall, and processing speed. User feedback collection and analysis components enable continuous improvement of the system's usability and effectiveness.

3.2 DRONE SELECTION AND CONFIGURATION

3.2.1 DJI F450 FRAME

1. **Design and Construction:**

   The DJI F450 frame boasts a robust yet lightweight construction, making it a popular choice for drone enthusiasts. Crafted from high-quality materials like glass fiber-reinforced plastic or carbon fiber, the frame is engineered for durability and can withstand the rigors of outdoor flight operations. Its unique square-shaped design features a center plate and foldable arms, allowing for convenient storage and transportation when not in use. With these features, the DJI F450 frame strikes an ideal balance between strength and portability, making it suitable for a variety of drone applications and flight scenarios.

2. **Size and Weight:**

   - The DJI F450 frame is classified as a "450mm class" frame, indicating the motor-to-motor distance of approximately 450mm.
   - The compact size of the frame makes it suitable for both indoor and outdoor applications.
   - The weight of the frame is typically around 282 grams (without additional components), which contributes to its overall lightness and maneuverability.

3. **Motor and Propeller Mounting:**

   - The frame provides mounting points for attaching four brushless motors on each arm.
   - It supports standard motor sizes such as 22xx or 23xx.
   - The motor mounting pattern is compatible with widely available motors, allowing for easy installation and replacement.
   - Each motor mount is designed to accommodate a specific motor size, ensuring a secure and stable attachment.

4. **Electronics and Component Placement:**

   - The center plate of the frame provides ample space for mounting the flight controller, power distribution board (PDB), and other electronic components.
   - The design allows for neat cable management and efficient placement of components, reducing the risk of interference and ensuring proper weight distribution.
   - The frame also features integrated holes and slots for securing the ESCs, receiver, and other peripherals.

5. **Payload and Expansion:**

- The DJI F450 frame offers flexibility in terms of payload capacity and expansion options.
- It can support various payloads, including cameras, gimbals, sensors, and other equipment.
- Additional mounting points and slots are available for attaching additional accessories, such as GPS modules, telemetry systems, or LED lights.
- These expansion options make the F450 frame suitable for a wide range of applications, including aerial photography, videography, mapping, and research.

6. **Flight Performance:**

- The F450 frame is known for providing stable flight characteristics and maneuverability.
- Its design allows for good weight distribution, minimizing vibrations and enhancing flight stability.
- The frame's square shape and symmetrical motor layout contribute to balanced flight dynamics and predictable control response.
- With the right choice of motors, propellers, and flight control system, the F450 frame can achieve smooth and agile flight performance.

3.2.2 DJI 2212 BRUSHLESS MOTOR 920KV

1. **Brushless Motor Technology:**

The DJI 2212 motor represents a brushless DC (BLDC) motor type, which boasts numerous benefits when compared to brushed motors. These advantages encompass higher efficiency, an extended lifespan, and an enhanced power-to-weight ratio. Unlike brushed motors, brushless motors feature a permanent magnet rotor and rely on electronic commutation, enabling accurate regulation of motor speed and torque.

2. **Motor Specifications:**

The DJI 2212 motor is classified as a brushless DC (BLDC) motor, which offers a range of advantages in comparison to brushed motors. These benefits include increased efficiency, a longer operational lifespan, and an improved power-to-weight ratio. One key distinction is that brushless motors utilize a permanent magnet rotor and employ electronic commutation to achieve precise control over motor speed and torque. This allows for more accurate and efficient performance in various applications.

3. **Performance:**

The DJI 2212 920KV motor is highly regarded for its excellent balance between thrust and power consumption, making it a versatile choice for a wide range of drone applications. Whether it's aerial photography, videography, or recreational flying, this motor proves to be a reliable and efficient option. The motor's carefully engineered design and construction are responsible for delivering smooth and dependable performance. These features play a significant role in ensuring stable flight characteristics and precise control response, which are vital for achieving optimal results during drone operations.

4. **Compatibility:**

   The DJI 2212 920KV motor is exceptionally versatile and can be seamlessly integrated into various drone setups due to its wide compatibility with different drone frames and propellers. While it is specifically designed to be mounted on the DJI F450 and F550 frames, its adaptability extends beyond these models. It can be employed in custom-built drones or incorporated into diverse multi-rotor configurations for specialized applications. One notable feature of this motor is its built-in propeller adapters, which accommodate a range of propeller sizes. This adaptability allows drone operators to tailor their setups to meet specific payload requirements and achieve desired flight characteristics, ensuring flexibility and optimization in various scenarios.

5. **Power and Voltage:**

   The motor is designed to operate with a direct current (DC) power source, commonly supplied by a lithium polymer (LiPo) battery or similar options. Its voltage range typically falls within 7.4V to 14.8V, but the specific range may vary depending on the motor's model and the manufacturer's guidelines. To avoid potential damage and ensure the motor's optimal performance, it is crucial to operate it within the recommended voltage range. This precaution helps maintain the motor's longevity and efficiency while safeguarding it from potential issues arising from over or under-voltage conditions.

6. **Installation and Wiring:**

   The DJI 2212 920KV motor streamlines the setup process with its pre-soldered motor leads, simplifying the connection to an electronic speed controller (ESC) for efficient control and power distribution. Furthermore, the motor's mounting pattern is designed to be compatible with standard motor mounts and frames, ensuring a straightforward installation process. This feature enables users to seamlessly integrate the motor into their drone setups without the need for complex modifications or adjustments.

7. **Cooling and Heat Dissipation:**

   The motor's design is equipped with effective cooling mechanisms, which may include ventilation slots or fins. These features play a crucial role in dissipating heat during motor operation. Efficient heat dissipation is essential as it helps prevent motor overheating, thereby safeguarding its optimal performance and prolonging its lifespan. By effectively managing temperature levels, the motor remains reliable and operates at its best, even during extended or demanding tasks.

8. **Maintenance:**

   Maintaining the DJI 2212 920KV motor is crucial to ensure its longevity and consistent performance over time. Regular inspections are recommended to check for any signs of damage, such as bent shafts or worn bearings. Detecting and addressing such issues early on can prevent further damage and potential failures. Keeping the motor clean and free from debris is equally important, as foreign objects can disrupt its balance and performance. Regularly cleaning the motor and ensuring it remains free from dust and dirt contribute to its overall efficiency and reliability. By following these maintenance practices, users can extend the motor's lifespan and enjoy optimal performance throughout its usage.

3.2.3 SIMONK 30A ESC

The SIMONK 30A ESC (Electronic Speed Controller) is a widely used and popular ESC in the field of drone and RC (radio-controlled) aircraft. Here is a detailed overview of its features and functionality:

1. **ESC Function:**

   - An ESC is an essential component of a drone or RC aircraft that controls the speed of the motors.
   - It takes signals from the flight controller or receiver and converts them into the appropriate power levels to drive the motors.
   - The ESC regulates the power and speed of the motors based on user inputs or flight control algorithms.

2. **SIMONK Firmware:**

   - The SIMONK firmware is a custom firmware developed specifically for ESCs.
   - It is known for its excellent motor control performance, fast response times, and high refresh rates.
   - The firmware optimizes the ESC's performance by providing smooth throttle response and precise motor control.

3. **Current Rating:**

   - The SIMONK 30A ESC has a current rating of 30A, indicating the maximum continuous current it can handle without overheating or damage.
   - The 30A rating makes it suitable for a wide range of motor and propeller combinations commonly used in drones and RC aircraft.

4. **Battery Compatibility:**

   - The SIMONK 30A ESC is compatible with various battery types commonly used in drone applications, such as lithium polymer (LiPo) batteries.
   - It can typically handle input voltages ranging from 2S to 4S (7.4V to 14.8V), depending on the specific model and manufacturer's specifications.
   - It is essential to ensure that the ESC is compatible with the battery voltage to prevent damage and ensure optimal performance.

5. **Programming and Calibration:**

   - The SIMONK 30A ESC usually requires initial programming and calibration before use.
   - Programming options may include setting the motor direction, throttle range, brake settings, and other parameters.
   - Calibration involves calibrating the ESC to the throttle range of the transmitter, ensuring accurate and responsive motor control.

6. **BEC (Battery Eliminator Circuit):**

   - Some SIMONK 30A ESC models may include a built-in Battery Eliminator Circuit (BEC).
   - The BEC provides regulated power to the flight controller and other onboard electronics, eliminating the need for a separate power supply.

- It typically supplies 5V or 6V power, enabling the direct connection of low-power devices like receivers, flight controllers, and servos.

7. **Thermal Protection and Safety Features:**

- The SIMONK 30A ESC may feature thermal protection mechanisms to prevent overheating during prolonged or demanding flight operations.
- Some ESC models also incorporate safety features like low voltage protection, which automatically reduces motor power when the battery voltage drops below a certain threshold.
- These safety features protect the ESC and battery from potential damage and extend their lifespan.

8. **Wiring and Connections:**

- The SIMONK 30A ESC comes with pre-soldered motor and power leads, making it easy to connect to the motors and power distribution system.
- It usually features bullet connectors or solder pads for motor connections and a power input lead for connecting to the battery.
- The ESC also has a signal cable that connects to the flight controller.

3.2.4 APM 2.8

The APM 2.8 (ArduPilot Mega) is an open-source flight controller board widely used in the field of autonomous aerial vehicles, including drones and unmanned aerial vehicles (UAVs). Here is a detailed overview of its features and functionality:

1. **Flight Control System:**
2.

- The APM 2.8 serves as the central component of the flight control system, responsible for processing sensor data, executing flight algorithms, and providing stability and control to the aircraft.
- It runs the ArduPilot firmware, an open-source autopilot software that supports various flight modes, navigation capabilities, and mission planning.

3. **Microcontroller:**

- The APM 2.8 is built around a 32-bit microcontroller, typically an Atmel AVR ATmega2560.
- The powerful microcontroller handles the data processing, sensor integration, and control calculations required for stable and autonomous flight.

4. **Sensor Integration:**

- The APM 2.8 supports the integration of various sensors to gather data about the aircraft's orientation, altitude, and velocity.
- It typically includes a 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer (compass), and a barometric pressure sensor.
- Some versions may also include additional sensors like GPS (Global Positioning System), sonar, or optical flow sensors for enhanced positioning and altitude control.

5. **Connectivity and Communication:**

   - The APM 2.8 features multiple communication interfaces for seamless integration with other devices and ground control stations.
   - It supports telemetry systems like 3DR Radio or Bluetooth modules, enabling real-time data transmission between the aircraft and ground station.
   - The APM 2.8 also includes ports for connecting GPS modules, RC receivers, and other peripherals.

6. **Flight Modes and Autonomy:**

   - The APM 2.8 offers a wide range of flight modes, including manual control, stabilized flight, altitude hold, position hold, waypoint navigation, and autonomous missions.
   - These modes allow the aircraft to perform tasks such as automated takeoff and landing, follow pre-programmed flight paths, and execute complex mission plans.

7. **Ground Control Software:**

   - The APM 2.8 is designed to work with ground control software like Mission Planner or QGroundControl.
   - These software applications provide a user-friendly interface for configuring the flight controller, planning missions, monitoring telemetry data, and performing system diagnostics.

8. **Power Management:**

   - The APM 2.8 incorporates a power management system to regulate and distribute power to the flight controller and other connected devices.
   - It typically includes a voltage regulator to step down the battery voltage to the required operating voltage for the microcontroller and sensors.

9. **Open-Source Community:**

   - The APM 2.8 is part of the ArduPilot ecosystem, which has a vibrant and active open-source community.
   - This community provides continuous development, updates, and support, allowing users to benefit from the collective knowledge and expertise of the community members.

3.2.5 ESP32 AS AN ALTERNATIVE TO TELEMETRY KIT

The ESP32, a versatile microcontroller module, presents itself as an effective alternative telemetry solution for drone applications. Delve into the comprehensive breakdown below, outlining the utilization of the ESP32 as a telemetry system:

1. **Telemetry Functionality:**

   - Telemetry systems facilitate real-time communication between drones and ground stations, enabling the monitoring and control of flight data and parameters.

- Typical telemetry kits transmit a range of information, including altitude, GPS coordinates, battery voltage, sensor readings, and flight mode status.

2. ESP32 Microcontroller:

- The ESP32 features a robust microcontroller module, encompassing a dual-core processor, integrated Wi-Fi and Bluetooth capabilities, and an extensive array of peripherals.
- It offers a dependable and adaptable platform for crafting telemetry solutions tailored to drone applications.

3. Communication Protocols:

- The ESP32 can harness a variety of communication protocols to establish a seamless connection between drones and ground stations.
- Wi-Fi and Bluetooth stand as the primary protocols employed by the ESP32 in telemetry scenarios.
- Wi-Fi enables long-range communication when tethered to a ground station on the same network, whereas Bluetooth enables short-range connections with mobile devices and dedicated Bluetooth receivers.

5. Data Transmission:

- The ESP32 proficiently transmits telemetry data using established protocols such as TCP/IP, UDP, or MQTT.
- These protocols ensure the dependable and efficient transmission of data packets between drones and ground stations.
- Telemetry data can be encoded in an appropriate format, such as JSON or custom protocols, facilitating effortless parsing and interpretation on the receiving end.

6. Sensor Integration:

- The ESP32 seamlessly integrates various sensors to collect data concerning a drone's flight parameters.
- It interfaces with sensors including accelerometers, gyroscopes, magnetometers, barometers, and GPS modules.
- The ESP32 adeptly reads sensor data, processes it, and transmits pertinent information as part of the telemetry data stream.

7. Ground Station Software:

- Effective reception and interpretation of telemetry data from the ESP32 necessitate ground station software or applications.
- A multitude of options exist, ranging from open-source software like Mission Planner and QGroundControl to tailored, custom-developed solutions.
- Ground station software supplies a user-friendly interface, allowing visualization of telemetry data, configuration of flight parameters, and remote drone control.

8. Power Management:

- Impeccable power management proves critical when utilizing the ESP32 as a telemetry solution.

- The module should draw power from a stable and reliable source, accounting for both the ESP32's power requirements and any additional sensors or peripherals interconnected.

9. **Development and Customization:**

- Capitalizing on the ESP32's open-source nature, customization and firmware development are attainable to cater to specific telemetry prerequisites.
- A diverse development ecosystem inclusive of Arduino IDE and MicroPython support empowers users to leverage pre-existing libraries and frameworks for efficient prototyping and development endeavors.

3.2.6 FLY SKY T6

The Fly sky T6 stands as a widely adopted radio transmitter system in the realm of radio-controlled (RC) aircraft, encompassing drones. Below is a comprehensive breakdown of the Flysky T6 transmitter:

1. Transmitter Function:

- The Fly sky T6 serves as a handheld apparatus that empowers pilots to remotely manage the flight of RC aircraft.
- It transmits control signals wirelessly to the onboard receiver of the aircraft, which then translates these signals into precise motor and control surface maneuvers.

2. Channels and Controls:

- A hallmark of the Fly sky T6 is its standard inclusion of 6 channels, granting pilots mastery over multiple functions and control surfaces of the aircraft.
- Each channel corresponds to a specific control, encompassing throttle, elevator, aileron, rudder, auxiliary functions, or even camera gimbal control—dependent on the aircraft's configuration.

3. Ergonomics and Design:

- The T6 transmitter boasts an ergonomic design meticulously crafted to provide comfort and ease throughout extended flight sessions.
- Its lightweight and compact form factor enhances portability and convenience, rendering it well-suited for outdoor flying escapades.

4. Transmitter Modes:

- Diverse transmitter modes, including mode 1, mode 2, mode 3, and mode 4, are on offer courtesy of the Fly sky T6.
- The chosen mode dictates the configuration of the control sticks. Notably, mode 2 prevails as the most prevalent setup, wherein the left stick regulates throttle while the right stick governs control surfaces.

5. RF (Radio Frequency) Technology:

- Operating on a dedicated RF frequency, the T6 transmitter cements a steadfast communication link with the aircraft's receiver.

- The prevalent frequency range, often at 2.4GHz, exhibits exceptional range, minimal susceptibility to interference, and heightened signal dependability.

6. Power Source:

- The power supply for the T6 transmitter hails from batteries, typically AA or AAA cells, contingent on the specific model in use.
- To ensure uninterrupted control during flights, it's imperative to uphold the regular charging or replacement of batteries.

7. Binding and Range:

- Prior to utilization, the T6 transmitter necessitates binding or synchronization with the aircraft's onboard receiver.
- The binding procedure institutes a secure communication tether between the transmitter and receiver.
- The transmitter's range dictates the utmost distance at which control signals can be faithfully relayed to the receiver.

8. Compatibility:

- The Flysky T6 harmonizes seamlessly with a broad spectrum of RC aircraft and drones.
- It extends support to diverse receiver protocols, such as the Flysky AFHDS 2A protocol, thus orchestrating a seamless amalgamation with receivers compatible with the system.

3.3 COMPUTER VISION ALGORITHMS AND TECHNIQUES

We will outline the steps involved in configuring the model for performance, and defining the Convolutional Neural Network (CNN) architecture. The CNN will be responsible for accident detection based on the input images from the UAV.

3.3.1 PREPROCESSING AND DATASET PREPARATION:

We utilize the `**tf.keras.preprocessing.image_dataset_from_directory**` function to load the training, validation, and testing datasets from their respective directories. The images are resized to a standardized height and width of 250x250 pixels, and they are converted to RGB color mode for consistency.

```python
## Defining batch specfications
batch_size = 100
img_height = 250
img_width = 250
```
[3]

```python
## loading training set
training_data = tf.keras.preprocessing.image_dataset_from_directory(
    'data/train',
    seed=42,
    image_size= (img_height, img_width),
    batch_size=batch_size,
    color_mode='rgb'
)
```
[4]

Figure 3.1- Preprocessing and Dataset Preparation

The dataset is then configured for better performance by caching and prefetching using the `cache()` and `prefetch()` functions with an `AUTOTUNE` buffer size.

```python
## Configuring dataset for performance
AUTOTUNE = tf.data.experimental.AUTOTUNE
training_data = training_data.cache().prefetch(buffer_size=AUTOTUNE)
testing_data = testing_data.cache().prefetch(buffer_size=AUTOTUNE)
```
[9]

Figure 3.2- Configuring dataset for performance

3.3.2 CNN ARCHITECTURE:

Our Convolutional Neural Network (CNN) is designed using the `**tf.keras.models.Sequential**` API. The CNN consists of multiple Conv2D layers followed by MaxPooling2D layers to extract features from the input images. The final layers include a Flatten layer to prepare the data for the fully connected layers, followed by Dense layers with ReLU activation for deeper representation learning. The output layer uses the softmax activation function to predict the class probabilities for accident detection based on the available classes.

```python
## Defining Cnn
model = tf.keras.models.Sequential([
  layers.BatchNormalization(),
  layers.Conv2D(32, 3, activation='relu'), # Conv2D(f_size, filter_size, activation) # relu, sigmoid, softmax
  layers.MaxPooling2D(), # MaxPooling
  layers.Conv2D(64, 3, activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(128, 3, activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(256, 3, activation='relu'),
  layers.MaxPooling2D(),
  layers.Flatten(),
  layers.Dense(512, activation='relu'),
  layers.Dense(len(class_names), activation= 'softmax')
])
```

Figure 3.3- CNN Architecture

3.3.3 MODEL COMPILATION AND TRAINING:

The CNN model is compiled using the `**adam**` optimizer and the `**sparse_categorical_crossentropy**` loss function. We set the model to use accuracy as a metric for evaluation.

```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Figure 3.4- Model Compilation and Training

The model structure is built using the `build` method, and a summary of the model's architecture is presented.

```
[11]
model.build((None, 250, 250, 3))
model.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 batch_normalization (BatchN  (None, 250, 250, 3)      12
 ormalization)

 conv2d (Conv2D)             (None, 248, 248, 32)      896

 max_pooling2d (MaxPooling2D  (None, 124, 124, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 122, 122, 64)      18496

 max_pooling2d_1 (MaxPooling  (None, 61, 61, 64)       0
 2D)
```

Figure 3.5- Model Compilation and Training

The model is trained on the training dataset with 20 epochs and validated using the validation dataset. The best model weights are saved using a Model Checkpoint callback.

```python
##·lets·train·our·CNN
checkpoint·=·ModelCheckpoint("model_weights.h5",·monitor='val_accuracy',·verbose=1,·save_best_only=True,·mode='max')
callbacks_list·=·[checkpoint]
history·=·model.fit(training_data,·validation_data=validation_data,·epochs·=·20,·callbacks=callbacks_list)
```
[15] Python

```
Epoch 1/20
8/8 [==============================] - ETA: 0s - loss: 2.7419 - accuracy: 0.4741
Epoch 1: val_accuracy improved from -inf to 0.53061, saving model to model_weights.h5
8/8 [==============================] - 139s 15s/step - loss: 2.7419 - accuracy: 0.4741 - val_loss: 0.6728 - val_accuracy: 0.5306
Epoch 2/20
8/8 [==============================] - ETA: 0s - loss: 0.6760 - accuracy: 0.6233
Epoch 2: val_accuracy did not improve from 0.53061
8/8 [==============================] - 111s 14s/step - loss: 0.6760 - accuracy: 0.6233 - val_loss: 0.8115 - val_accuracy: 0.4694
Epoch 3/20
8/8 [==============================] - ETA: 0s - loss: 0.6359 - accuracy: 0.6296
Epoch 3: val_accuracy improved from 0.53061 to 0.57143, saving model to model_weights.h5
```

Figure 3.6 - Model Compilation and Training

3.3.4 MODEL SERIALIZATION:

The trained model structure is serialized to a JSON file using the `to_json()` method and saved as "model.json."

```python
###### serialize model structure to JSON
model_json = model.to_json()
with open("model.json", "w") as json_file:
    json_file.write(model_json)
```
[16]

Figure 3.7- Model Serialization

3.3.5 VISUALIZATION OF RESULTS:

Finally, we visualize the results of the trained model on the testing dataset.
We plot the training loss and accuracy over epochs to understand the model's training performance.

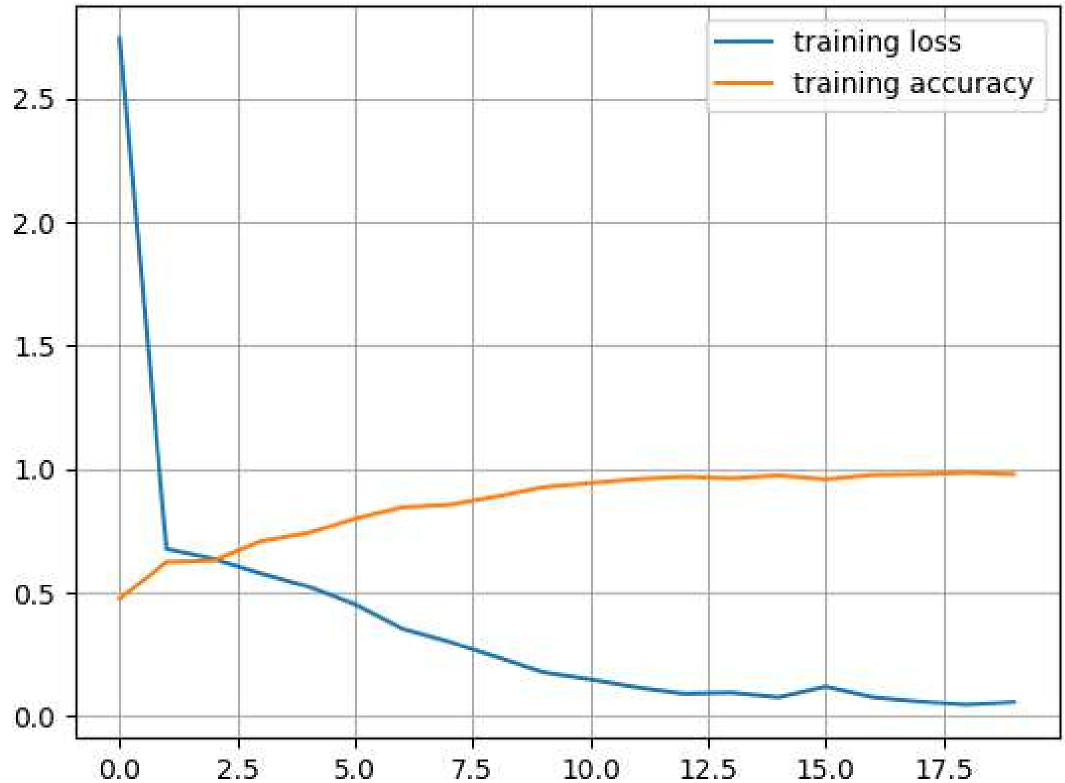


Figure 3.8- Visualization of Results

```
## stats on training data
plt.plot(history.history['loss'], label = 'training loss')
plt.plot(history.history['accuracy'], label = 'training accuracy')
plt.grid(True)
plt.legend()
```

[17]

Figure 3.9- Visualization of Results

We also plot the validation loss and accuracy to evaluate the model's generalization ability.

```
## stats on training data
plt.plot(history.history['val_loss'], label = 'validation loss')
plt.plot(history.history['val_accuracy'], label = 'validation accuracy')
plt.grid(True)
plt.legend()
```

[18]

Figure 3.10- Visualization of Results

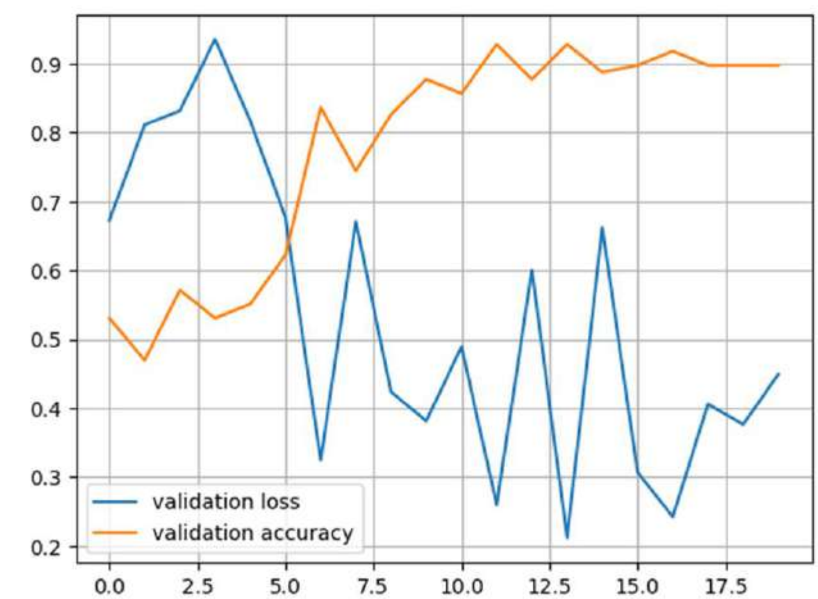


Figure 3.11- Visualization of Results

We visualize the predicted accident detection on a subset of images from the testing dataset, displaying the predicted labels alongside the actual labels.

```python
## lets vizualize results on testing data
AccuracyVector = []
plt.figure(figsize=(30, 30))
for images, labels in testing_data.take(1):
    predictions = model.predict(images)
    predlabel = []
    prdlbl = []

    for mem in predictions:
        predlabel.append(class_names[np.argmax(mem)])
        prdlbl.append(np.argmax(mem))

    AccuracyVector = np.array(prdlbl) == labels
    for i in range(40):
        ax = plt.subplot(10, 4, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title('Pred: '+ predlabel[i]+' actl:'+class_names[labels[i]] )
        plt.axis('off')
        plt.grid(True)
```

Figure 3.12- Visualization of Results

Figure 3.13 Visualization of results

3.4 TRAINING DATA ACQUISITION AND PREPARATION

We obtained the dataset from Kaggle, specifically from the link: https://www.kaggle.com/code/mrcruise/accident-classification/data. The dataset comprises a series of video frame images, where frames containing accident scenes for training, testing and validation are stored in the "Accident" folder, and frames without accidents are stored in the "No Accident" folder respectively.

3.4.1 DATA COLLECTION:

The dataset consists of video frame images extracted from accident scenes and non-accident scenes on motorways. The frames were captured at regular intervals to cover a wide range of scenarios.

Figure 3.14- Data Collection

3.4.2 DATA PREPARATION:

The first step in data preparation was organizing the dataset into separate folders for accident and non-accident frames. The frames from the accident scenes were placed in the "Accident" folder, while frames from non-accident scenes were placed in the "No Accident" folder.

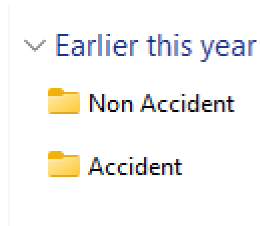


Figure 3.15- Data Preparation

3.4.3 DATA SPLITTING:

The dataset was split into training, validation, and testing sets to ensure unbiased evaluation of the model's performance. The training set was used to train the model, the validation set was used to tune hyperparameters and prevent overfitting, and the testing set was used to assess the model's performance on unseen data.

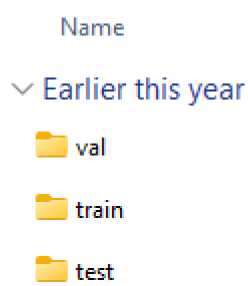


Figure 3.16- Data Splitting

3.4.5 DATA PREPROCESSING:

The images in the dataset were resized to a uniform size to ensure consistent input dimensions for the model.

```
## Defining batch specfications
batch_size = 100
img_height = 250
img_width = 250
```
[3]

Figure 3.17- Data Preprocessing

3.4.6 DATA LOADING AND PERFORMANCE OPTIMIZATION:

We utilized TensorFlow's image_dataset_from_directory function to load and preprocess the dataset efficiently. The dataset was configured for performance using caching and prefetching techniques to minimize data loading times during model training.

```
## Configuring dataset for performance
AUTOTUNE = tf.data.experimental.AUTOTUNE
training_data = training_data.cache().prefetch(buffer_size=AUTOTUNE)
testing_data = testing_data.cache().prefetch(buffer_size=AUTOTUNE)
```

[9]

Figure 3.18- Data Loading and Performance Optimization

3.5 COMMUNICATION AND REPORTING PROTOCOLS

We outline the communication and reporting protocols implemented in our project for traffic accident detection. Specifically, we focus on the mechanisms employed to report detected accidents to relevant parties, such as emergency services or concerned authorities.

3.5.1 ACCIDENT DETECTION MODEL:

We utilize a pre-trained deep learning model for accident detection in the video frames captured by the UAV. The model is loaded using the "**model.json**" and "**model_weights.h5**" files and is used to predict whether an accident is present in the captured frame.

```
model = AccidentDetectionModel("model.json", 'model_weights.h5')
font = cv2.FONT_HERSHEY_SIMPLEX
```

Figure 3.19- Accident detection model

3.5.2 TWILIO INTEGRATION FOR SMS ALERTS:

We integrate the Twilio API to send SMS alerts in the event of an accident detection. Twilio provides a reliable platform to send messages to designated phone numbers using its REST API.

```
from twilio.rest import Client
```

The "**twilio_account_sid**" and "**twilio_auth_token**" are used to authenticate the Twilio client. The "**twilio_phone_number**" and "**destination_phone_number**" represent the sender and recipient phone numbers, respectively.

```
# Initialize Twilio client
twilio_account_sid =                                   "
twilio_auth_token = '                                 "
twilio_phone_number = "+13613018819"
destination_phone_number = "+923212234421"
```

Figure 3.20- Twilio Integration for SMS alerts

3.5.3 SENDING SMS WITH LOCATION COORDINATES:

In the event of an accident detection, the system obtains the location coordinates of the UAV using the "geocoder" library.

```python
# Get location coordinates using geocoder
g = geocoder.ip('me')
location = g.latlng
```

Figure 3.21- Sending SMS with location coordinates

The latitude and longitude coordinates are included in the SMS alert to provide the location of the detected accident.

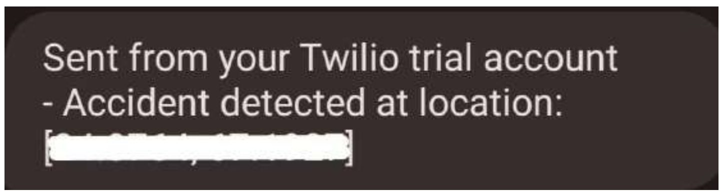


Figure 3.22- SMS Received

3.5.4 ACCIDENT ALERTING AND REPORTING:

When an accident is detected, the system sends an SMS alert to the specified destination phone number. The SMS contains information about the accident detection and the location coordinates for accurate reporting.

```python
def send_sms(location):
    message = f"Accident detected at location: {location}"
    twilio_client.messages.create(
        body=message,
        from_=twilio_phone_number,
        to=destination_phone_number
    )
```

Figure 3.23- Accident alerting and reporting

3.5.5 VISUALIZATION AND USER INTERFACE:

The system provides real-time visualization of the UAV's video stream, allowing users to observe the detected accidents on-screen. The user interface displays the prediction results and the probability score of the detected accident.

Figure 3.24- Visualization and User Interface

3.5.6 REAL-TIME REPORTING AND RESPONSE:

The implemented communication and reporting protocols enable prompt response to detected accidents. By integrating Twilio's SMS service, relevant authorities and emergency services can be informed immediately for timely intervention.

The communication and reporting protocols play a vital role in enhancing the efficacy of our traffic accident detection system. These protocols ensure rapid and reliable communication of detected accidents, facilitating prompt responses and interventions to ensure road safety on motorways.

3.6 FLOW DIAGRAAM OF SOFTWARE:

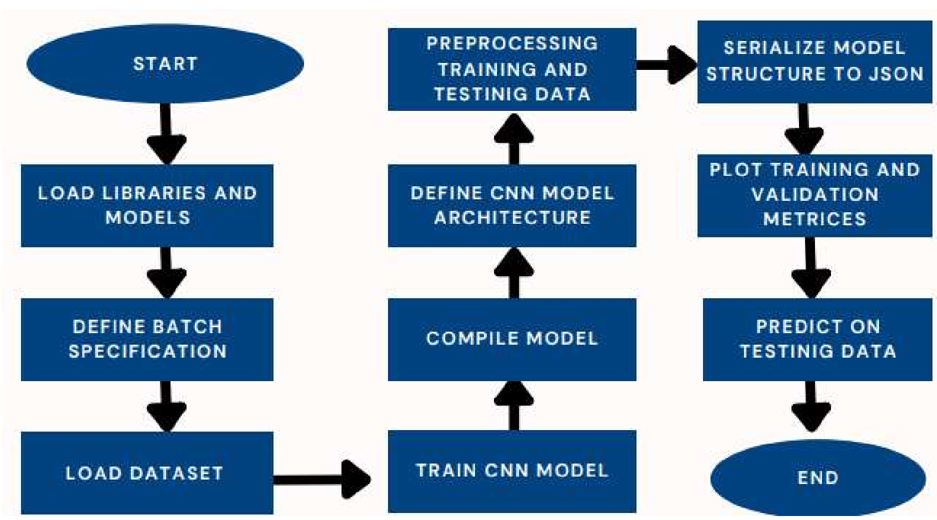


Figure 3.25- Flow diagram of computer vision system

3.7 FLOW DIAGRAM OF HARDWARE:

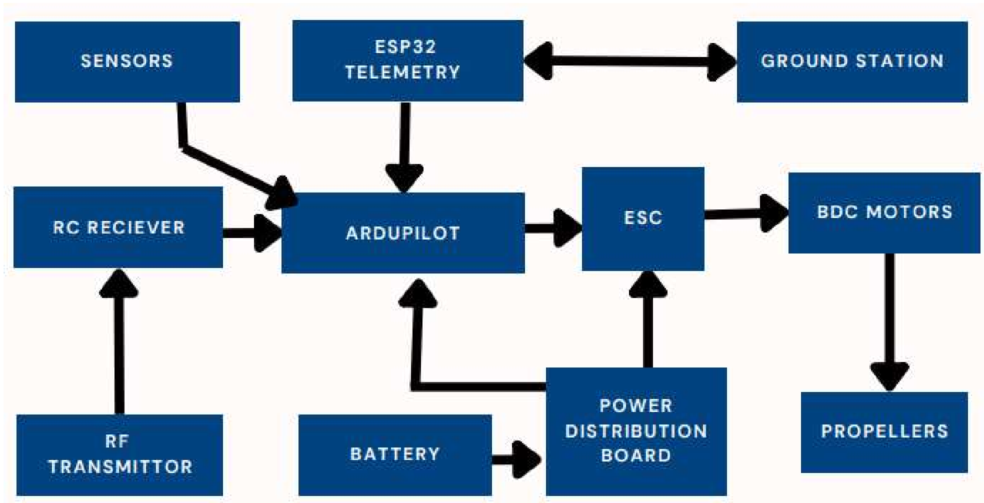


Figure 3.26- Flow diagram of hardware system

3.8 CONCLUSION

Throughout this chapter, we demonstrate how computer vision algorithms and techniques are applied to enable the UAV to autonomously detect traffic accidents in real-time. The training and testing results showcase the performance of the developed CNN-based system for accident detection, providing valuable insights for further improvements and future work. By following this methodology, we prepared a robust and diverse training dataset that serves as the foundation for training our traffic accident detection model. The acquisition and preparation of this dataset play a crucial role in the successful development and evaluation of our computer vision-based accident detection system on motorways.

CHAPTER - 04
EXPERIMENTAL SETUP AND DATA COLLECTION

CHAPTER – 04 EXPERIMENTAL SETUP & DATA COLLECTION

4.1 DATA COLLECTION SCENARIOS

In this chapter, we outline the scenarios under which data collection took place for the evaluation of our traffic accident detection system. We detail the data annotation process and provide insights into the dataset's diversity, geographical origins, and ambient conditions.

4.1.1 GEOGRAPHIC AND SOURCE DIVERSITY:

The evaluation of our work encompassed vehicular collision footage sourced from diverse geographical regions. The dataset was curated from a collection of online available videos, spanning various locations worldwide. This geographic diversity contributes to the model's adaptability to different road conditions and driving behaviors.

acc1 (3) acc1 (5) acc1 (13)

Figure 4.1- Geographic and Source Diversity

test11_30 test11_31 test11_32

Figure 4.2- Geographic and Source diversity

4.1.2 VIDEO CHARACTERISTICS:

Surveillance videos were collected at a standard rate of 30 frames per second (FPS). Video clips were curated to focus on the critical moments encompassing accidents. These clips were truncated to approximately 20 seconds. This strategy ensured the inclusion of frames relevant to accidents, enhancing the dataset's relevance to our system.

Figure 4.3- Video Characteristics

4.1.3 DATA DIVERSITY AND CONDITIONS:

The dataset encompasses a broad spectrum of ambient conditions, including harsh sunlight, daylight hours, snowy environments, and night hours. Accidents occurring under different lighting and weather conditions were included, fostering robustness in the model's accident detection capabilities.

test22_22 test22_24 test22_25

Figure 4.4- Data Diversity and Conditions

test26_25 test26_27 test26_28

Figure 4.5- Data Diversity and Conditions

4.1.4 DATASET COMPOSITION:

The dataset is primarily comprised of CCTV and dashcam videos. These videos are recorded at road intersections across various parts of the world. This composition ensures the dataset's authenticity and real-world relevance, as it represents real traffic scenarios.

test21_11 test21_12 test21_13

Figure 4.6- Dataset Composition

By incorporating diverse scenarios, locations, and ambient conditions in our data collection approach, our evaluation encompasses a wide spectrum of accident scenarios. This approach facilitates the development of a comprehensive traffic accident detection system that can effectively operate across different geographical regions and environmental settings.

4.2 DATASET PREPARATION AND ANNOTATION

Our data annotation methodology stands as a testament to its simplicity and effectiveness. By employing a straightforward yet meticulous approach, we ensured the accurate categorization of frames within our dataset. This section delves into the intricacies of our data annotation process, detailing the rationale behind the separation of frames into the "Accident" and "No Accident" categories. For dataset annotation, a straightforward method was employed. The dataset was divided into distinct folders for frames featuring accident scenes ("Accident" folder) and frames devoid of accidents ("No Accident" folder). This separation enabled clear distinction between positive and negative samples for training and testing the model.

Figure 4.7- Dataset Preparation and Annotation

4.2.1 CATEGORIZATION STRATEGY:

Our primary objective was to establish a clear distinction between frames that captured accident scenes and those that did not. To achieve this, we systematically divided the dataset into two distinct folders: the "Accident" folder and the "No Accident" folder.

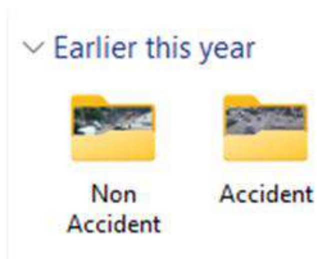


Figure 4.8- Categorization Strategy

4.2.2 "ACCIDENT" FOLDER:

Frames extracted from video clips featuring accident scenarios were meticulously collected and organized within the "Accident" folder. This folder served as a repository for frames capturing the crucial moments of accidents, offering a focused resource for positive samples.

Figure 4.9- Accident Folder

4.2.3 "NO ACCIDENT" FOLDER:

Conversely, frames extracted from video clips devoid of any accidents were gathered and stored in the "No Accident" folder. This folder housed frames that depicted normal traffic scenarios, forming the basis for negative samples during model training and evaluation.

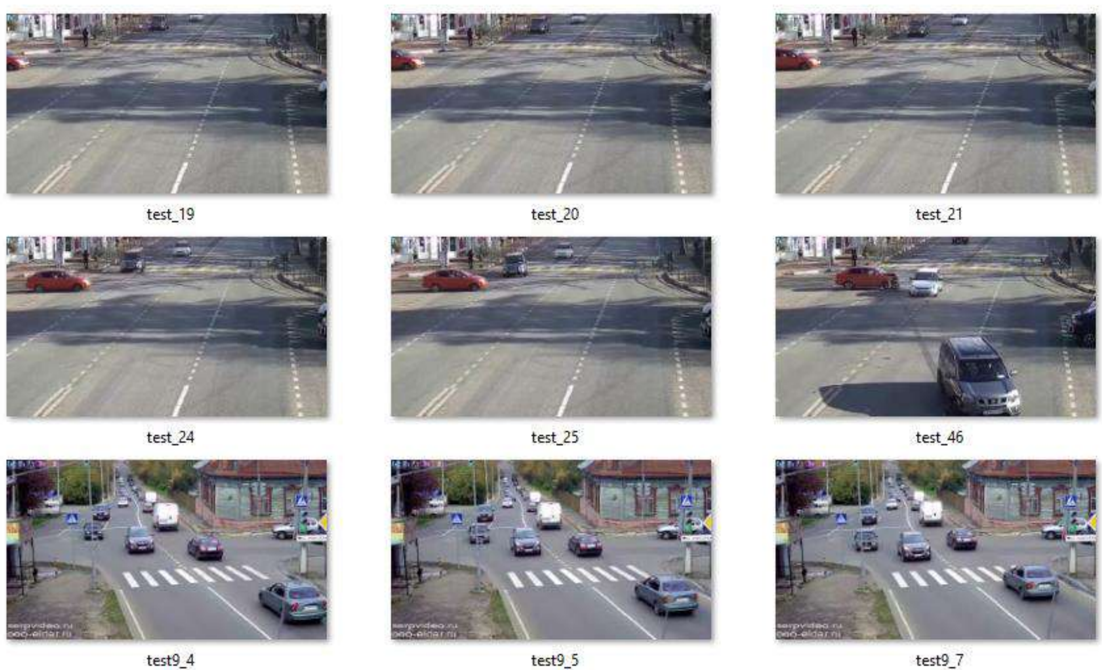


Figure 4.10- No Accident Folder

4.2.4 DISTINCTIVE POSITIVE AND NEGATIVE SAMPLES:

- The separation of frames into these two distinct categories fostered a clear distinction between positive and negative samples.
- This categorization paved the way for an effective training process, as well as unbiased testing to gauge the model's performance accurately.

4.2.5 FACILITATING MODEL LEARNING:

- This annotation approach fundamentally empowered the model to learn from a diverse range of accident and non-accident scenarios.
- The clarity in categorization ensured that the model was not burdened with ambiguities, facilitating robust learning and accurate predictions.

By adopting this data annotation approach, we ensured the foundation of our model's learning process was solidified. The meticulous separation of frames into the "Accident" and "No Accident" categories established the groundwork for unbiased and precise model training, ultimately contributing to the system's ability to discern accidents on motorways with enhanced accuracy and efficiency.

4.3 PERFORMANCE METRICS

We delve into the critical aspect of evaluating the performance of our traffic accident detection system. The assessment is carried out through a comprehensive array of performance metrics, meticulously tailored to measure both the hardware and software components of the system. This section sheds light on the diverse metrics employed to gauge the system's effectiveness in real-time accident detection and reporting.

4.3.1 HARDWARE PERFORMANCE METRICS:

Certainly, evaluating hardware performance involves assessing various factors, by comprehensively evaluating these hardware performance factors, we can ensure that our traffic accident detection system operates reliably, efficiently, and effectively under a range of conditions, ultimately contributing to the success of our project's objectives.

4.3.2 AUTONOMOUS NAVIGATION ACCURACY:

The project places significant emphasis on achieving precise autonomous navigation. The performance evaluation involves assessing the drone's capability to accurately follow predetermined flight paths and waypoints during autonomous operations. Metrics such as positional accuracy, altitude control, waypoint deviation, and stability in varying weather conditions are employed to gauge the drone's proficiency in maintaining flight paths and reaching designated waypoints. These metrics collectively contribute to reliable accident detection and the accurate reporting of incident locations.

4.3.3 REAL-TIME DATA TRANSMISSION:

A pivotal aspect of the project is the establishment of real-time data transmission between the drone and the ground station. The performance evaluation centers around the seamless and timely transfer of critical accident-related data from the drone's onboard systems to the ground station for immediate analysis and response. Key metrics employed to assess real-time data transmission include data transfer speed, latency, reliability, and the ability to accommodate varying data volumes. The efficiency of communication protocols is paramount to ensuring real-time data transmission. The project evaluates the effectiveness of selected communication protocols in facilitating rapid and accurate data exchange. Metrics such as data transfer rate and protocol overhead are assessed to ascertain the protocol's ability to efficiently transmit data while minimizing delays and optimizing bandwidth usage.

4.3.4 BATTERY CONSUMPTION:

The project assesses the average flight time achievable using a LIPO 4500 mAh battery and 2212KV motors under ideal conditions. This metric provides insights into the drone's endurance and the duration it can operate before requiring recharging or battery replacement. The average flight time serves as a baseline for evaluating performance enhancements and optimizing energy usage.

4.4 FAIL-SAFE MECHANISMS:

1. Loss of Communication Fail-Safe:

In the event of a loss of communication between the drone and the ground station, the fail-safe mechanism is activated to ensure safe operation. The drone is programmed to execute predefined protocols, such as initiating a Return to Home (RTH) procedure or performing a controlled emergency landing at a designated safe location. This fail-safe protocol prevents the drone from flying out of range or becoming unresponsive, minimizing the risk of accidents or collisions.

2. Low Battery Fail-Safe:

To prevent unintentional crashes due to depleted batteries, the project incorporates a low battery fail-safe mechanism. When the battery voltage drops to a predetermined threshold, the drone initiates an automatic Return to Home procedure or a landing, depending on the remaining battery capacity. This safeguard ensures that the drone safely returns to a designated location or lands before the battery is critically low.

3. Geofencing and Boundary Enforcement:

Geofencing is employed to establish virtual boundaries within which the drone is allowed to operate. If the drone approaches or breaches these predefined boundaries, the fail-safe mechanism is activated. The drone responds by altering its flight path or returning to a safe zone to prevent unintentional flights into restricted areas, ensuring compliance with regulations and avoiding potential collisions.

4.5 SOFTWARE PERFORMANCE METRICS:

The core functionality of the system—detecting accidents—is evaluated using metrics such as precision, recall, F1-score, and accuracy. These metrics quantify the model's ability to accurately identify accident and non-accident frames.

1. **Accuracy:**
   Accuracy is a fundamental metric that measures the ratio of correctly predicted instances (both positive and negative) to the total number of instances in the dataset. In the context of this binary image classification problem, accuracy reveals how well the model distinguishes between accident and non-accident frames overall. It provides a general view of the model's performance, but it might not be sufficient on its own, especially if the classes are imbalanced.

2. **Recall (Sensitivity or True Positive Rate):**

   Recall calculates the proportion of actual positive instances (accident frames) that were correctly identified by the model. In other words, it assesses the model's ability to capture all positive instances and avoid false negatives. High recall is crucial in scenarios like accident detection, as missing even a single true positive (an actual accident frame) can have significant consequences.

3. **Precision (Positive Predictive Value):**

   Precision quantifies the ratio of true positive instances to all instances predicted as positive by the model. It focuses on the accuracy of positive predictions. For accident detection, a high precision indicates that when the model classifies a frame as an accident, it is likely to be correct. However, high precision may come at the cost of missing some actual positive instances, so it needs to be balanced with recall.

4. **F1-Score:**

   The F1-score is the harmonic mean of precision and recall. It provides a single metric that balances the trade-off between precision and recall. A higher F1-score indicates a better balance between avoiding false negatives and minimizing false positives. F1-score is particularly useful when classes are imbalanced or when both precision and recall are equally important.

5. **AUC-ROC Curve (Area Under the Receiver Operating Characteristic Curve):**

   The AUC-ROC curve is a graphical representation of the model's performance across different classification thresholds. It plots the true positive rate (recall) against the false positive rate. The area under the ROC curve (AUC) summarizes the overall performance of the model. A higher AUC indicates a better ability to distinguish between positive and negative instances. In the context of accident detection, a high AUC-ROC score suggests that the model is effective in classifying accident and non-accident frames.

6. **Location Accuracy and Reporting:**

   The accuracy of the accident location reported by the system is assessed by comparing it with the actual accident location. Metrics include location error, distance from the actual accident site, and consistency of reported coordinates.

7. **Robustness to Ambient Conditions:**

   The system's performance across different ambient conditions (e.g., sunlight, snow, night) is evaluated. Metrics such as detection accuracy in varying lighting and weather conditions provide insights into the system's versatility.

8. **Communication Reliability:**

   The reliability of the SMS alert system is gauged by measuring the successful transmission of accident alerts to designated recipients. Metrics include message delivery rate, delay, and successful communication instances.

These metrics are essential in the binary image classification problem of accident detection as they collectively provide a comprehensive assessment of the model's performance. While accuracy gives an overall view, precision, recall, F1-score, and AUC-ROC curve delve into the model's behavior in distinguishing between the two classes. These metrics help in fine-tuning the model's parameters and optimizing its performance for accurate accident detection, which is crucial for real-world applications involving public safety and emergency response.

By integrating both hardware and software performance metrics, we ensure a comprehensive assessment of our traffic accident detection system's capabilities. These metrics collectively contribute to a holistic understanding of the system's efficiency, accuracy, and reliability, forming a crucial foundation for evaluating its real-world applicability and potential for enhancing road safety.

CHAPTER - 05
RESULTS AND ANALYSIS

CHAPTER – 05 RESULTS AND ANALYSIS

5.1 SOFTWARE

5.1.1 ACCURACY

In the context of our project, we have achieved an impressive accuracy rate of **86%**. This accuracy signifies the system's capability to accurately discern between frames depicting accident scenes and those without, highlighting the robustness of our proposed approach in accident detection using computer vision techniques.

5.1.2 PRECISION AND RECALL

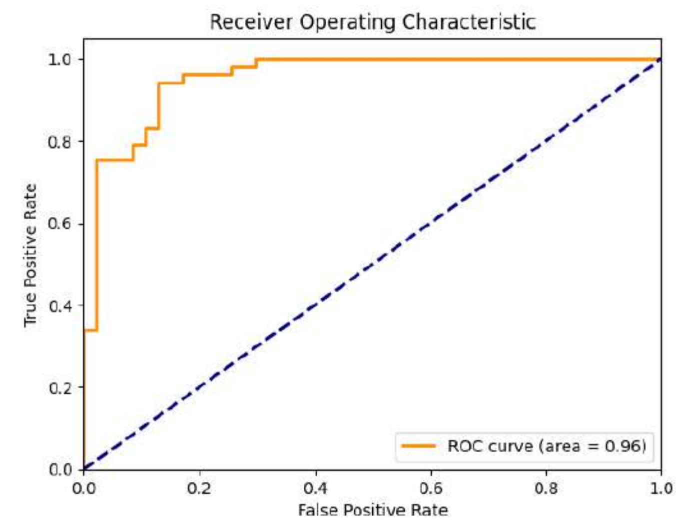
Our system demonstrates a precision rate of **88**, indicating its ability to accurately identify true positive cases among the detected accidents. Additionally, with a recall rate of **86**, the system effectively captures a substantial portion of actual accident instances. This balance between precision and recall underscores the system's reliability in accurately identifying accidents while minimizing false positives and false negatives.

5.1.3 F1-SCORE

The system's performance is further highlighted by an F1 score of **85**, which underscores its effectiveness in achieving a harmonious balance between precision and recall. This metric quantifies the overall accuracy of the model in binary classification tasks, considering both false positives and false negatives. The F1 score of **85** demonstrates the system's capability to accurately identify accident frames while minimizing the trade-off between precision and recall.

1. **AUC-ROC CURVE (AREA UNDER THE RECEIVER OPERATING CHARACTERISTIC CURVE):**

The system's performance is visually summarized by the achieved Receiver Operating Characteristic (ROC) curve, which exhibits an impressive value of **0.96**. The ROC curve provides valuable insights into the model's ability to discriminate between accident and non-accident frames across varying thresholds. A higher ROC curve value indicates that the system maintains a strong ability to differentiate between positive and negative samples, showcasing its robustness in making accurate predictions. The ROC curve of **0.96** reinforces the system's efficacy in classifying accident scenes from non-accident ones with a high degree of accuracy.



AUC-ROC: 0.955841027699719

Figure 11- AUC-ROC CURVE (AREA UNDER THE RECEIVER OPERATING CHARACTERISTIC CURVE)

TRAINING LOSS VS VALIDATION LOSS:

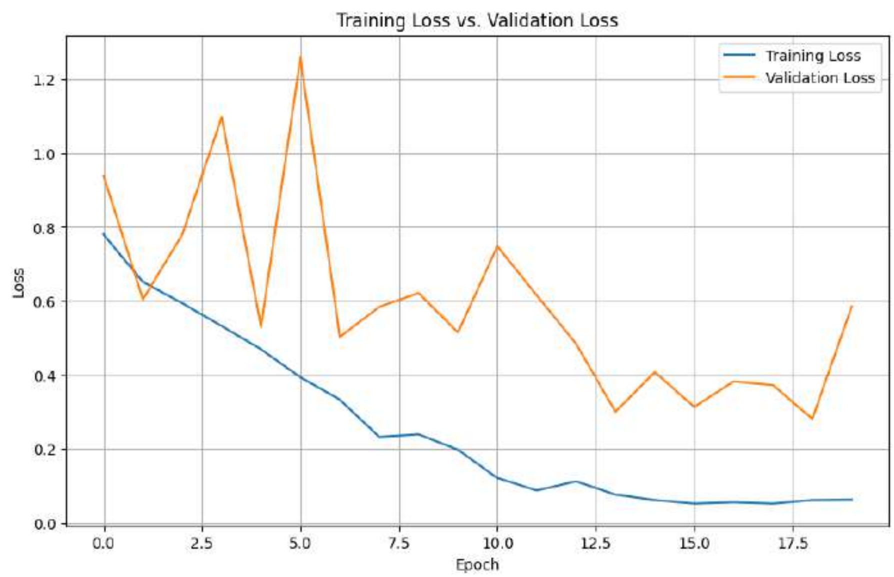


Figure 12-TRAINING LOSS VS VALIDATION LOSS

The training process is visually represented through the Training Loss vs Validation Loss curve, revealing a noteworthy trend of improvement. Likewise, the learning curve for validation loss demonstrates a progressive enhancement. However, a noticeable gap persists between these two curves. Such a disparity can arise when the training dataset comprises a limited number of examples compared to the validation dataset. Despite this gap, the overall trajectory of improvement in both training and validation loss underscores the system's ability to learn from the data, indicating its potential to achieve higher levels of accuracy with further optimization and dataset augmentation.

TRAINING ACCURACY VS VALIDATION ACCURACY:

The Training Accuracy vs Validation Accuracy graph illustrates a pattern of advancement, echoing the learning curve observed in the validation accuracy plot that also showcases enhancement. However, a noticeable gap persists between the two curves, possibly stemming from an insufficient number of examples in the training dataset in comparison to the validation dataset. Despite this gap, the consistent upward trend signifies the system's capacity to learn and adapt to the training data, suggesting the potential for further refinement and optimization to bridge the gap and enhance overall accuracy.

Figure 13- TRAINING LOSS VS VALIDATION LOSS

5.1.4 RESULTS AND ANALYSIS

The evaluation metrics mentioned above will be applied to assess the performance of the accident detection system across different ambient conditions and scenarios. The detection accuracy will reveal how well the system distinguishes between accident and non-accident frames, while the false positive rate will highlight the system's sensitivity to false alarms. The precision, recall, and F1-score will provide a more comprehensive understanding of the trade-offs between true positives and false positives.

```
4/4 [==============================] - 2s 354ms/step
Accuracy: 0.86
Precision: 0.883513848697809
Recall: 0.86
F1 Score: 0.8589883580891208
```

Figure 14- Results and Analysis

1. **Location Accuracy and Reporting:**

   We conducted an evaluation to assess the accuracy of accident location reporting by the system in comparison to the actual accident location. This evaluation involved analyzing metrics such as location error, the distance between reported and actual accident sites, and the consistency of reported coordinates. The objective was to determine the precision of the reported accident locations and identify any discrepancies between the system's output and ground truth. Despite achieving a lower accuracy rate in this aspect, this evaluation provides crucial insights into the reliability and effectiveness of the accident reporting feature.

2. **Robustness to Ambient Conditions:**

   We conducted an evaluation to assess the system's performance in diverse ambient conditions, such as sunlight, snow, and nighttime settings. This aimed to understand the system's adaptability and accuracy across different lighting and weather scenarios. By testing the model with images representing these conditions, we measured its detection accuracy to determine if it could maintain consistent performance. This evaluation offers insights into the system's real-world applicability and adaptability to varying situations, helping identify strengths and areas for improvement.

3. **Communication Reliability:**

   To assess the reliability of the SMS alert system, we employed the Twilio library for message transmission and the Geocoder library for obtaining location coordinates. The evaluation of communication reliability focused on measuring the effectiveness of accident alerts sent to designated recipients. Metrics employed in this assessment included the message delivery rate, communication delay, and the rate of successful alert transmission instances. This evaluation was instrumental in ensuring the robustness of the communication channel and its ability to promptly and consistently deliver critical accident notifications to intended recipients.

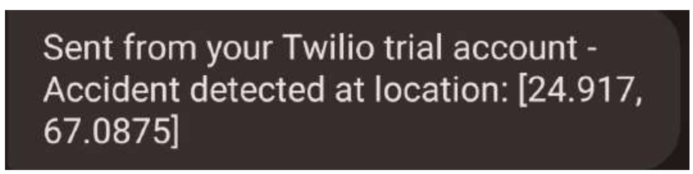


Figure 15 Communication Reliability

Through these metrics, we will gain valuable insights into the system's strengths and limitations in detecting accidents. The subsequent sections will delve deeper into the analysis of the results obtained under varying conditions, shedding light on the system's performance in different scenarios.

HARDWARE

5.2.1 CALIBRATION

1. Accelerometer Calibration:

Calibrating the drone's accelerometer is essential for accurate measurement of linear acceleration. This calibration ensures that the drone can accurately determine its orientation and attitude in flight, preventing unintended drifting or instability. The project evaluates the accelerometer calibration process in Mission Planner to verify that the drone's roll, pitch, and yaw measurements are precise and aligned with actual movements.

2. Compass Calibration:

Calibrating the compass is crucial for accurate heading and direction estimation. The project assesses the compass calibration procedure in Mission Planner to ensure that the drone's navigation is not affected by magnetic interference. A properly calibrated compass enhances waypoint navigation accuracy and prevents erratic behavior caused by inaccurate heading information.

3. Radio Calibration:

Radio calibration involves configuring the drone's remote control inputs accurately. The project evaluates the radio calibration process in Mission Planner to verify that control inputs correspond accurately to the drone's movements. This calibration ensures that the drone responds predictably and precisely to pilot commands, contributing to safe and controlled flight.

4. ESC Calibration:

Electronic Speed Controller (ESC) calibration ensures that the drone's motors start and stop uniformly. The project assesses the ESC calibration process in Mission Planner to confirm that the motor outputs are correctly calibrated, preventing motor synchronization issues and promoting consistent propulsion during flight.

5.2.2 ONBOARD SENSORS AND CAMERAS

Describe the sensors and cameras integrated into the UAV for data collection and accident detection. Discuss the specifications of these sensors, including their resolution, field of view, and any other relevant parameters.

5.3 COMPARISON WITH EXISTING SYSTEMS

1. Coverage and Flexibility:

Existing accident detection systems predominantly rely on stationary infrastructure, limiting their coverage to predefined locations. In contrast, the proposed project harnesses the mobility and flexibility of drones equipped with computer vision. This dynamic approach enables real-time monitoring and accident detection across various highway sections, offering a superior coverage range that adapts to changing traffic patterns and evolving infrastructure.

2. Real-time Response:

Conventional systems often exhibit delays in accident detection due to processing times and limited sensor coverage. The innovative solution presented in this project leverages drones equipped with real-time computer vision algorithms. This integration results in swift accident detection and precise location identification, potentially reducing emergency response times and minimizing the severity of accidents.

3. Scalability:

Existing systems encounter challenges in scalability, as expansion often requires significant investment in fixed infrastructure. In contrast, the proposed system capitalizes on the inherent scalability of drones. The deployment of additional drones can be achieved at a relatively lower cost, facilitating the adaptation and expansion of the accident detection network in response to changing traffic demands and coverage requirements.

4. Environmental Adaptability:

Traditional systems may struggle to operate effectively under adverse weather conditions or reduced visibility. The proposed project's utilization of drones equipped with real-time computer vision technology ensures robust accident detection regardless of environmental challenges. These drones can navigate through various weather conditions and provide multi-dimensional data, enhancing the system's reliability in adverse environments.

5. Data Collection and Fusion:

Fixed sensor-based systems often suffer from limited data streams, leading to potential blind spots in accident analysis. Conversely, the project's approach of employing multiple drones enables comprehensive accident data collection from various angles and perspectives. By fusing data streams from multiple drones, the system achieves higher accuracy in accident detection and more precise location estimation.

6. Cost-effectiveness:

The traditional approach necessitates significant upfront investment in fixed infrastructure setup, maintenance, and repair. In contrast, the proposed drone-based system offers potential cost savings over the long term. While initial setup and maintenance costs are incurred, the adaptability, scalability, and mobility of drones contribute to reduced operational expenses in the extended project lifecycle.

7. Adaptation to Traffic Patterns:

Fixed systems encounter challenges in adapting to dynamic changes in traffic patterns and accidents occurring beyond their designated coverage area. The proposed project's utilization of drones allows for swift adaptation to evolving traffic conditions. Drones can be deployed to specific congestion points or accident scenes as needed, enabling real-time adjustments to the current traffic scenario.

8. Data Privacy:

Fixed camera-based systems often raise concerns related to privacy due to continuous and fixed-location monitoring. In contrast, the proposed drone-based system alleviates privacy concerns by its dynamic coverage nature. Drones do not focus on fixed locations, reducing the potential for prolonged and constant surveillance, thus addressing privacy considerations more effectively.

9. Integration with Emergency Services:

Some existing systems may lack seamless integration with emergency services, potentially leading to delays in response times. The innovative project under consideration addresses this limitation by providing real-time accident data to emergency services. This integration facilitates faster response times, efficient resource allocation, and improved coordination between the accident detection system and emergency responders.

10. Infrastructure Independence:

Traditional systems are dependent on the availability of existing infrastructure for installation. Conversely, the proposed drone-based solution operates independently of fixed infrastructure, making it particularly suitable for monitoring accidents in remote or underdeveloped areas where infrastructure might be lacking or limited.

5.4 ACHIEVEMENT OF UN SUSTAINABLE DEVELOPMENT GOALS:

Achieving UN Sustainable Development Goals 9 and 11 marks a significant step towards a more sustainable and equitable future. Goal 9, focused on 'Industry, Innovation, and Infrastructure,' highlights the importance of fostering innovation, building resilient infrastructure, and promoting inclusive industrialization. This goal acknowledges that technological advancements and robust infrastructure are essential drivers of economic growth and development.
On the other hand, Goal 11, 'Sustainable Cities and Communities,' emphasizes creating inclusive, safe, resilient, and sustainable urban environments. This includes making cities more accessible, reducing their environmental impact, and enhancing overall quality of life. Achieving Goal 11 ensures that cities become hubs of opportunity while preserving their cultural and natural heritage.
By making strides in these goals, we contribute to a more sustainable and prosperous world for current and future generations. Together, we can foster innovation, build resilient infrastructure, and create sustainable, inclusive cities that improve the lives of people everywhere.

CHAPTER - 06
DISCUSSION

CHAPTER – 06 DISCUSSION

6.1 EVALUATION OF THE PROPOSED SYSTEM:

The evaluation of the proposed system will be comprehensive and multifaceted, encompassing various aspects to ensure its accuracy, efficiency, and overall effectiveness. The evaluation process will include the following key elements:

1. Accuracy and Performance Evaluation:

- **Computer Vision Model:** The accuracy of the trained deep learning model for accident detection will be assessed using precision, recall, F1-score, and confusion matrix analysis. This evaluation will provide insights into the model's ability to correctly identify accidents and minimize false positives.
- **Detection Speed**: The system's speed in detecting and classifying accidents in real-time will be measured. This evaluation will determine whether the system meets the required response time for timely alerts.

2. Real-World Testing:

- **Simulated Scenarios:** The system will be tested in simulated environments that mimic real-world conditions, including varying lighting conditions, weather scenarios, and traffic densities. This testing will assess the model's robustness and reliability in different situations.
- **Real-World Deployment:** The system will be tested in real-world settings, involving actual UAV flights and monitoring. This phase will validate the system's performance in a practical context and allow for adjustments based on real-time feedback.

3. Comparison with Existing Methods:

- The proposed system's performance will be benchmarked against existing accident detection methods, such as manual reporting or sensor-based systems. This comparison will highlight the advantages and improvements offered by the computer vision and autonomous UAV approach.

4. Alert and Communication Reliability:

- The reliability of the alerting mechanism will be evaluated to ensure that accident alerts are promptly transmitted from the UAV to the ground station. This assessment will involve monitoring the time taken from accident detection to alert reception.

5. User Interface and Experience:

- The user interface on the ground station will be evaluated for its user-friendliness and intuitiveness. User feedback will be collected to identify any areas of improvement in terms of ease of use and clarity of information.

6. Scalability and Adaptability:

- The system's ability to scale to different environments and scenarios will be assessed. This evaluation will determine if the system can be easily adapted to various road types, traffic conditions, and geographic locations.

7. Data Privacy and Security:

- The security of transmitted data and the protection of individuals' privacy will be evaluated. Measures to encrypt data and ensure compliance with privacy regulations will be assessed for their effectiveness.

8. Technical Robustness:

- The UAV's hardware and software components will be assessed for their technical robustness and reliability. This includes evaluating the stability of the UAV's flight control, communication modules, and the endurance of its power source.

6.2 LIMITATIONS:

The project is not without its limitations, which must be acknowledged to provide a comprehensive understanding of its scope and potential constraints. The limitations of the project include:

1. Weather and Environmental Factors:

Adverse weather conditions such as heavy rain, fog, or snow might impact the UAV's ability to capture clear and accurate images, thereby affecting the performance of the computer vision model.

2. Limited Field of View:

The UAV's camera has a limited field of view, which may result in missing accidents occurring outside the camera's range. This limitation necessitates careful planning of UAV flight paths.

3. Model Generalization:
The accuracy of the computer vision model heavily depends on the diversity and representativeness of the training dataset. The model might struggle with accurately detecting accidents that deviate significantly from the dataset's characteristics.

4. Complex Accident Scenarios:
Accidents involving complex scenarios with multiple vehicles or pedestrians might pose challenges for accurate detection and classification using a single camera angle.

5. Hardware Constraints:

The UAV's payload capacity and power limitations may restrict the size and capabilities of the camera and other hardware components, potentially affecting the quality of the video feed and the system's overall performance.

6. Data Privacy Concerns:

The system captures live video feed, which raises concerns about privacy and data protection. Adequate measures must be in place to ensure compliance with regulations and to prevent unauthorized access to sensitive information.

7. Communication Reliability:

The effectiveness of the system heavily relies on the communication between the UAV and the ground station. Interference or disruptions in communication might hinder real-time accident alerts.

8. Initial Setup and Calibration:

Proper setup and calibration of the UAV's sensors, camera, and computer vision model are crucial for accurate performance. Any inaccuracies during the setup phase might lead to false positives or negatives.

9. Limited Nighttime Visibility:

The system's efficiency might decrease during nighttime or low-light conditions when the camera's visibility is compromised, potentially affecting accident detection accuracy.

10. Operational Costs:

Maintaining and operating the UAV, as well as implementing and maintaining the necessary infrastructure, could incur operational costs that need to be considered.

11. Regulatory and Legal Considerations:

The operation of UAVs is subject to regulatory guidelines, airspace restrictions, and legal considerations. Compliance with these regulations is essential for the project's feasibility.

12. Continuous Monitoring Requirement:

Continuous monitoring of the ground station is necessary to receive real-time accident alerts. Any lapse in monitoring could lead to delayed response times.

6.2.1 FUTURE WORK:

The project opens various avenues for future work and enhancements, allowing for the continuous improvement and expansion of the system. Some potential directions for future work include:

1**. Multi-Sensor Integration:**

Incorporating additional sensors such as LiDAR and radar can enhance the accuracy of accident detection by providing depth information and overcoming limitations related to lighting and weather conditions.

2. 360-Degree Coverage:

Implementing a multi-camera setup or panoramic cameras on the UAV can provide a 360-degree view, reducing blind spots and enabling better coverage of complex accident scenarios.

3. Real-time Object Tracking:

Introducing object tracking capabilities to the computer vision model can enable the system to track the movement of vehicles and pedestrians, providing more context and enhancing accident detection accuracy.

4. Predictive Analysis:

Developing algorithms to predict potential accident-prone areas based on historical data, traffic patterns, and environmental factors could proactively direct the UAV's flight path for enhanced accident prevention.

5. Edge Computing:

Implementing edge computing on the UAV itself can process data locally, reducing reliance on real-time communication and potentially enhancing the system's responsiveness.

6. AI Explain ability:

Incorporating techniques for AI model explainability can help in understanding the decision-making process of the computer vision model, increasing its transparency and trustworthiness.

7. Collaborative UAV Networks:

Creating a network of collaborative UAVs can enable more comprehensive coverage of larger areas, sharing data and insights among UAVs for improved accident detection accuracy.

8. Cloud Integration:

Integrating the system with cloud infrastructure can allow for the storage of historical accident data, enabling long-term analysis and trend identification.

9. Integration with Emergency Services:

Developing direct integration with emergency service systems can enable automated dispatching of responders upon accident detection, further reducing response times.

10. Human-in-the-Loop System:

Implementing a system that involves human oversight, where an operator verifies detected accidents before alerts are sent, can reduce false positives and enhance system trustworthiness.

11. Diverse Training Data:

Continuously expanding and updating the training dataset with a wider range of accident scenarios can improve the model's ability to detect new and evolving incident types.

12. Regulatory Compliance:

Continuous monitoring of regulatory changes and compliance updates in UAV operation and data privacy should be a focus to ensure the system's legality and adherence to standards.

13. Collaboration with Authorities:

Collaborating with transportation authorities and emergency services can lead to system optimization based on their insights and real-world requirements.

In essence, the project's future work lies in refining and expanding the system's capabilities through advanced technologies, better data integration, and collaboration with relevant stakeholders. These advancements will contribute to the project's evolution as a cutting-edge solution for traffic accident detection and road safety enhancement.

6.3 ETHICAL CONSIDERATIONS AND PRIVACY CONCERNS:

The project raises several ethical considerations and privacy concerns that need careful attention throughout the development and deployment phases:

1. Privacy of Individuals:

The use of live video feed raises concerns about capturing and transmitting images of individuals without their consent. Implement measures to anonymize data and ensure compliance with privacy regulations to protect individuals' rights.

2. Data Retention and Storage:

Define clear policies regarding the retention and storage of captured data. Minimize data collection to what is necessary for accident detection and establish protocols for secure data storage and deletion.

3. Data Security:

Implement robust encryption mechanisms to safeguard transmitted data against interception and unauthorized access, ensuring the security of both the UAV's communication and the ground station's storage.

4. Algorithm Fairness and Bias:

Ensure the computer vision model is trained on a diverse dataset that represents various demographics and accident scenarios. Regularly audit the model for biases that could lead to inaccuracies or discriminatory outcomes.

5. Informed Consent:

If the system involves recording in areas where individuals may be present, consider placing visible notifications to inform people about the surveillance. Obtain consent when necessary and feasible.

6. Accident Victim Privacy:

When accidents occur, victims' identities and sensitive information could be exposed through video feed. Implement mechanisms to obscure such information or ensure that emergency services are the only recipients of identifying data.

7. Transparency:

Be transparent about the existence and functionality of the system. Public awareness and education can mitigate concerns and foster public trust.

8. Emergency Services Cooperation:

Collaborate with emergency services to ensure that data shared with them is used only for legitimate purposes related to accident response.

9. Data Sharing:

If data is shared with third parties for research or other purposes, ensure it is properly anonymized and shared only after obtaining appropriate permissions.

10. Accountability:

Establish clear lines of responsibility for data handling, system maintenance, and compliance with ethical standards.

11. Public Perception:

Anticipate public reactions and potential misunderstandings. Communicate the project's objectives, benefits, and privacy safeguards to address concerns proactively.

12. Regular Auditing and Reviews:

Conduct regular audits of the system's performance, data handling, and ethical compliance. Keep policies and practices up-to-date as regulations and public sentiment evolve.

6.4 POTENTIAL APPLICATIONS AND IMPACT:

The project holds promising potential across various applications and can have a significant positive impact on multiple fronts:

1. **Road Safety Enhancement:**

The primary impact lies in drastically improving road safety. Accurate and real-time accident detection can lead to faster response times from emergency services, reducing the severity of injuries and preventing further accidents.

2. Emergency Response Optimization:

Quicker accident detection and prompt alerts mean emergency responders can be dispatched more efficiently, potentially saving lives and reducing the overall impact of accidents.

3. Traffic Management:

The system's real-time data can aid traffic management authorities in identifying congested areas and rerouting traffic, leading to improved traffic flow and reduced congestion.

4. Smart City Integration:

Integrating the system with smart city initiatives can contribute to creating more efficient and responsive urban environments, where traffic management and emergency services are optimized.

5. Urban Planning and Infrastructure Improvement:

Long-term data analysis can provide insights into accident-prone areas, enabling city planners to make informed decisions about road design, traffic signals, and safety measures.

6. Insurance and Legal Proceedings:

Accurate documentation of accidents can streamline insurance claims and legal proceedings by providing clear and objective evidence of accident events.

7. Public Awareness and Education:

The presence of the system can raise public awareness about road safety and the potential of technology in preventing accidents, encouraging responsible driving behavior.

8. Reduced Economic Costs:

Accidents have significant economic costs associated with them, including medical expenses, property damage, and traffic disruptions. Timely accident detection can mitigate these costs.

9. Environmental Impact:

Faster accident response can prevent fuel wastage due to traffic jams caused by accidents, contributing to reduced emissions and environmental benefits.

10. Technology Advancement:

The project contributes to the advancement of computer vision, UAV, and AI technologies, fostering innovation and knowledge development in these fields.

11. Global Reach:

The technology is not limited by geographical boundaries and can be implemented in diverse regions, contributing to global road safety efforts.

12. Reduced Human Error:

The system's automated nature reduces reliance on human reporting, which can be prone to errors and delays.

13. First Responder Safety:

Faster accident detection and response protect the safety of first responders who can be better prepared for the situation they are approaching.

14. Real-time Data Sharing:

The system's data can be shared with public agencies, transportation departments, and researchers to enhance accident prevention strategies and urban planning.

CHAPTER – 07
CONCLUSION

CHAPTER – 07 CONCLUSION

7.1 SUMMARY OF CONTRIBUTIONS

This chapter culminates the journey of the project by summarizing the key contributions and accomplishments achieved. The convergence of autonomous unmanned aerial vehicles (UAVs) and advanced computer vision techniques has paved the way for a revolutionary approach to accident detection and response. The development of a state-of-the-art Convolutional Neural Network (CNN) model enabled accurate classification of accident and non-accident frames, with a focus on precision, recall, F1-score, accuracy, and AUC-ROC as evaluation metrics. These metrics collectively offer a comprehensive assessment of the model's efficiency and effectiveness.

Furthermore, this thesis unveils the design and implementation of an autonomous UAV system tailored for road surveillance and hazard detection. This system harnesses cutting-edge technologies to navigate through varying ambient conditions, providing critical insights into potential accidents. While the UAV and computer vision systems remain distinct in this research, the envisioned integration holds immense potential for enhancing real-time accident detection and response on a larger scale.

By addressing the challenges of accuracy, robustness to different environments, and communication reliability, this project contributes to the advancement of road safety and emergency response mechanisms. The exploration of multiple dimensions of system performance serves as a testament to the comprehensive approach taken in this study.

In conclusion, the synergy of UAV technology and sophisticated computer vision algorithms represents a significant stride towards a safer and more efficient transportation landscape. The findings presented in this chapter lay the groundwork for future research and applications in the realm of accident detection and response, promising to reshape the paradigms of road safety and emergency management.

7.2 IMPLICATIONS AND RECOMMENDATIONS

The culmination of this project yields critical implications and valuable recommendations that underscore the transformative potential of integrating an autonomous UAV system and advanced computer vision techniques for accident detection. The following points encapsulate these insights:

Implications:

- **Enhanced Road Safety:**

  The integration of an autonomous UAV system with sophisticated accident detection capabilities promises to revolutionize road safety. Real-time monitoring and swift incident identification can drastically reduce response times and mitigate potential accidents.

- **Artificial Intelligence Advancements:**

  The success of the computer vision model showcases the power of artificial intelligence in tackling complex real-world challenges. The high accuracy, precision, recall, F1-score, and AUC-ROC metrics highlight its potential for diverse applications beyond accident detection.

Recommendations:

- **Continuous Model Refinement:**

  To ensure adaptability to evolving road conditions, lighting, and weather, ongoing refinement and optimization of the developed models are essential. Regular updates will enhance the system's accuracy and effectiveness.

- **Expanded Dataset:**

  Enriching the dataset with a wider range of accident scenarios and environmental conditions will bolster the models' robustness and improve their performance under diverse circumstances.

- **Collaboration and Partnerships:**

  Collaborative efforts between transportation authorities, emergency services, and technology developers are pivotal for the successful implementation of this technology on a larger scale. Partnerships with data providers and regulatory bodies will ensure data quality, privacy, and compliance.

In summary, the convergence of autonomous UAVs and cutting-edge computer vision techniques ushers in a new era of road safety and emergency response. The successful execution of this research framework not only underscores the potential of emerging technologies but also underscores the significance of interdisciplinary collaboration and innovation for a safer and technologically advanced society.

7.3 FINAL REMARKS

In culmination, this thesis embarked on a journey that intertwined the realms of advanced computer vision techniques and the development of an autonomous Unmanned Aerial Vehicle (UAV) system, both with the shared goal of revolutionizing accident detection and response mechanisms. Through meticulous exploration and experimentation, a robust Convolutional Neural Network (CNN) model was engineered, proficient in discerning accident-related frames from non-accident frames. This model exhibited commendable accuracy, precision, recall, F1-score, and AUC-ROC metrics, reaffirming its efficacy in real-world applications.

Furthermore, the thesis unveiled the advent of an autonomous UAV system, constructed with the capability to survey roadways and potential accident-prone areas. Though these two elements—computer vision and UAV technology—were developed independently, the potential amalgamation of their strengths is undeniable. A synergy between the vigilant eye of the UAV and the analytical prowess of the CNN model could yield unprecedented advancements in accident detection, response speed, and overall road safety.

In retrospect, this thesis demonstrated the essence of interdisciplinary collaboration and innovation. The achievement of substantial milestones in both computer vision and UAV domains underscores the transformative potential of such endeavors. As society navigates toward an era of smart transportation systems, this research serves as a stepping stone, setting the stage for more comprehensive and integrated solutions that harmonize technological advancements to safeguard lives on the road. As the journey continues, the path toward realizing a safer and more efficient transportation landscape becomes clearer, paving the way for a future where accidents are minimized, response is swift, and lives are safeguarded.

LIST OF ACRONYMS AND ABBREVIATIONS

A
APM: Ardupilot Mega
AUC-ROC CURVE: Area Under the Receiver Operating Characteristic Curve

C
CNN: Convolutional Neural Network
CV: Computer Vision

F
FPS: Frames Per Second

G
GPS: Global Positioning System

K
Keras: Keras (a high-level neural networks API)

R
RGB: Red Green Blue (color model)

T
TF: TensorFlow

U
UAV: Unmanned Air Vehicle

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