

Automated Injury Detection and Alert Systems in Public Transportation Integrating IoT with Convolutional Neural Networks

S P Vimal

Department of Electronics and Communication Engineering,
Sri Ramakrishna Engineering College,
Coimbatore, Tamil Nadu, India
vimal.sp@srec.ac.in

G. Bhuvaneswari

Professor, Department of Computer Science and Engineering, Saveetha Engineering College, Chennai, Tamil Nadu, India
bhuvankerani@gmail.com

John Benito Jesudasan Peter

Senior Manager,

Cyber | Data Science & Engineering,
Capital One Services, LLC,
Richmond, Virginia, USA
johnbenitoauthor@gmail.com

G. Manikandan

Professor, Department of Artificial Intelligence and Data Science,
RMK Engineering College,
Chennai, Tamil Nadu, India
mani4876@gmail.com

U. Kavitha

Assistant Professor,
School of Commerce, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India
drkavithau@veltech.edu.in

Thamizhamuthu R

Assistant Professor, Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur Campus-Chengalpattu, Chennai, Tamil Nadu, India
thamizhr@srmist.edu.in

Abstract—Innovative methods to improve public transportation safety and response mechanisms have emerged due to Internet of Things (IoT) and artificial intelligence (AI) technologies. IoT devices and Convolutional Neural Networks (CNNs), a class of deep learning algorithms analyzing visual imagery, are used to create an innovative Automated Injury Detection and Alert System (AIDAS) for public transportation. The proposed AIDAS architecture employs IoT sensors and cameras in buses and trains to monitor and evaluate passengers' physical health in real time. These sensors can detect unexpected impacts, odd motions, and distressing noises. A strong CNN model trained to detect passenger injury or bodily damage receives live images from the onboard cameras. An automatic alarm process is activated immediately upon injury detection. The closest emergency response teams and transportation system operators get complete event reports, including time, position (by GPS coordinates), and injury type. A quick reaction to accidents with this real-time alarm system might save lives and reduce public transportation injuries. AIDAS' use of IoT and CNN technology is innovative in public transportation safety. The technology significantly improved emergency response times and reduced unattended injuries in public transport networks. The system's excellent damage detection accuracy is due to CNNs' advanced image processing and pattern recognition skills and IoT devices' sensory inputs. It also addresses privacy issues and the necessity for strong data encryption and proposes solutions. Finally, it analyzes how AIDAS affects public transportation safety and future research and development in this critical field.

Keywords— Real-Time Monitoring, Emergency Response, Deep Learning, Sensor Networks, Visual Imagery Analysis, Public Transit Security

I. INTRODUCTION

Major traffic violations include reckless driving, which may be caused by drivers being sleepy, under the influence of drugs or alcohol, changing lanes without signaling, or going faster than the speed limit [1]. Many innocent persons are hurt or killed because of these car accidents caused by

reckless driving. To reduce the drivers' incentive to take on more and more passengers by introducing a regulated online payment system on the buses using an Android app.

Public bus drivers in Thailand are notoriously irresponsible and often drive faster than the speed limit, leading to a high number of traffic accidents involving these vehicles [2]. Waiting for the bus when its whereabouts and arrival time are unclear is only one example of the many issues with public transportation. Researchers are recommending an NB-IoT-based intelligent bus management system as a solution to this issue. To achieve its stated goals, it will investigate, plan, and build an NB-IoT smart bus management system; thereafter, it will evaluate the system's evolution, study related works and comparisons, and assess the system's efficiency.

Injuries were assessed using the Abbreviated Injury Scale, which considers the acceleration curves of the head, and the forces and moments felt by the upper necks of the occupants after impact [3]. Through direct head impact during rollover, simulation findings show passengers positioned near the rollover window are more likely to sustain severe injuries compared to those positioned on the gangway [8]. Although skull fractures are unlikely, severe axial neck stress poses a deadly danger of neck injury. Although the bus complies with regulations may significantly lessen the severity of crash injuries.

Pedestrians may be detected by autonomous vehicles using a variety of sensors to a high degree of precision. Road accidents might happen if any sensor fails to work [4]. Because pedestrians are particularly susceptible to harm in traffic accidents to quantify the degree of harm sustained by pedestrians in autonomous bus-pedestrian collisions using finite element modelling. different kinds of vehicle impacts and assessed the likelihood of injuries to the head and chest. It examined how the speed of the vehicle affected the likelihood of danger. Researchers discovered frontal impacts

were more harmful than side impacts, and pedestrians' bodies were hurt more by greater velocities.

During the month of May in 2012, the dynamic test of the school bus seat was carried out [5]. According to the statistics of the test results, the research offered some insight into the injuries sustained by the occupants. It was determined via the examination of test curves and films there are two hypotheses on the causes of injuries. It was decided to do some simulation work in order to investigate the impact of important design aspects.

The injury mechanism of bus passengers during rollover accidents was examined by analyzing the causes of the accidents and the rolling process [6]. A crucial collision force model and a rollover velocity model were developed, and rollover incidents were categorized as either tripped or un-tripped. To determine where the cars were, the roller model was used. Researchers looked at the most common areas of damage for people in rollover accidents, including the spine, chest, pelvis, and head. Findings aid in determining the root causes of injuries sustained by bus passengers and provide pointers for accident reconstruction efforts.

The problem of the HIC criteria being employed and its critical values being inaccurate was brought [7]. The study led to the discovery the injury safety determined by the HIC does not correlate to the injury security determined by the Wayne State curve, which was referred to by the individuals who developed this criteria. This was discovered as a consequence of the findings of the research. Using technologies are based on artificial intelligence, the findings may be used in intelligent systems to provide assistance with decision-making about the selection criteria for road safety systems.

II. LITERATURE REVIEW

Investigating the variables influences the severity of injuries sustained by drivers of both passenger cars and trucks in collisions involving this kind of vehicle [8]. In Canada, data on accidents recorded by police is compiled from 2007 to 2017. To simulate two-vehicle accidents remove those involving a single passenger car and a single truck. Injuries of varying severity levels are underrepresented. This work employs a hybrid methodology, over-sampling, under-sampling, and a cost-sensitive learning technique to tackle the data imbalance problem. It utilizes five different categorization models to compare the performance.

Bicycle helmets are recommended by several nations to reduce the likelihood of injury [9]. To conduct systematic with emphasis analysis to investigate the efficacy of bicycle helmets. The present study begins by reviewing the results of research that have used meta-analyses to examine data from bicycle accidents. The second part of the article discusses the results considering previous studies have used simulation to evaluate the efficacy of bicycle helmets; the third part provides supplementary material in the form of important methodological papers dealing with cycling and the many elements contribute to the severity of injuries.

It discusses the transport accident radioactive material leak risk assessment model [10]. Transport accident statistics data and severity rating are used to establish a quantitative evaluation approach for radioactive materials release rate.

Gauss Model air dispersion predicts fire accident consequences from radioactive material release accidents. The approach and statistical accident data are used to implement one example. The evaluation approach provided a preliminary quantitative estimate for transport radioactive material discharge accidents.

Road transport incidents involving hazardous materials are very dangerous and may cause harm to people, their property, and the environment [11]. To decrease mortality rates and enhance traffic safety, it is important to examine the variables influence road transport accidents involving hazardous chemicals. This will assist identify the primary causes of these accidents and contribute to the adoption of specific and targeted solutions. To examine data on accidents involving the transportation of hazardous materials from seven different locations of China using the eXtreme Gradient Boosting method.

Particularly in the months following massive disasters like earthquakes, the combined capacity of ambulances in major cities is sometimes insufficient to meet the demand [12]. Still, it's not sensible to keep the ambulance capacity greater than normal; given how seldom earthquakes are in various towns. Consequently, protecting life during these catastrophes depends on the efficient use of ambulances. Consequently, the purpose of this study is to provide a strategy for efficiently transporting the greatest number of catastrophe victims to hospitals within the allotted time.

Real-time public transit monitoring in Bangladesh and India is in high demand. Bangladesh's growing workforce and student population demand secure travel [13]. Culture uses the IoT to secure homes and businesses. Bus owners prioritize passenger safety and driver and local bus monitoring. Local transit is also a problem in the nation, like speeding, which causes many road accidents. It's can geofence country's local busses by integrating GPS tracking with automated safety system. It will describe computer vision and real-time data analysis surveillance system concept and prototype.

A traffic accident hinders both movement and access to emergency medical services [14]. In an effort to reduce the overall amount of time it takes to provide aid to accident victims, looked at a route planning tool uses information from aeromedical centers. It offers a KNN-select method that takes viewpoint into account, and it includes information like aircraft plans, ambulance locations, and hospitals. In order to maximize the allocation of resources propose the primary support bases and priority areas of help, along with a prototype that uses available data from airfields, helipads, hospitals, and accidents.

An approach based on probability to assess the seismic resistance of transportation networks in the event of a medical emergency [15]. Through the smooth integration of probabilistic danger, risk, and agent-based modules, the framework calculates the overall social losses suffered by the community in terms of injuries and deaths. The intensity of the ground shaking and failure is used by the hazard module to describe the earthquake. By calculating the amount of debris, injuries, and early deaths, as well as the reaction and damage to different infrastructure components and buildings, the risk module assesses the community's first post-earthquake situation. The module mimics the steps of an emergency response team, including finding and saving

lives, treating injuries, getting hospitals back up and running, and cleaning up after accidents.

III. PROPOSED SYSTEM

The proposed approach overcomes problems with existing injury detection systems by using IoT and CNNs for real-time monitoring for improving accuracy, reducing reaction times, and lowering human error, eventually enhancing passenger safety in public transportation environments.

A. Methodology

Improved passenger safety and quicker response times in an emergency may be achieved with the help of the proposed system. This system integrates the growing number of IoT sensors with CNNs to provide a system for real-time monitoring and alerting in the transportation network. In AIDAS, the IoT sensors and cameras are installed in various public transportation vehicles, including trains, buses, and subways. These sensors have been carefully engineered to pick up on a variety of danger signs, such as sudden motions, hits, or distress noises, all of which might indicate an injury or the possibility of one.

Select CNNs for their enhanced image recognition proficiency, facilitating efficient injury evaluation in real-time conditions. CNN examines visual input, automatically extracting features to identify patterns, enabling accurate injury evaluation in public transit situations. CNN models are continuously analyzing visual data provided by the cameras' live video feeds. The CNNs, a subset of deep neural networks known for their superior visual image processing and analysis capabilities, are trained using massive datasets of video and image data reflecting a range of damage situations seen in public transit.

Due to their training, CNNs can now identify certain patterns and traits linked to injuries, such as passengers displaying weird postures, falling, or exhibiting other symptoms of discomfort. Immediate detection of possible injuries is made possible by the integration of CNNs with real-time video data, which significantly outperforms the speed and accuracy of standard surveillance systems. An automatic alarm procedure is initiated by the system upon detection of possible harm or danger of injury. Following this, a thorough incident report is created outlining the details of the observed occurrence, including exact time stamps and the vehicle's position (as determined by GPS). The control center of the public transportation system and emergency response teams get this information in real-time, allowing for quick evaluation and deployment of any required medical or support services to the scene of the accident.

This real-time alert system is critical for making sure that injuries are treated quickly, which might save lives and make injuries far less severe because of the faster reaction times. The AIDAS leverages a multi-pronged strategy for public transit safety by using both IoT and CNN models. The IoT components provide a constant flow of sensor data, shedding light on the vehicle's physical state and external variables, while CNNs give visual data interpretation with unmatched precision. Using two technologies at once improves the system's injury detection capabilities and knowledge of the dynamics of safety in public transportation settings.

There are several serious issues with the security of public transportation that AIDAS solves. The system lessens the burden of manual monitoring, which may be prone to oversight and delays, by automating the detection and alarm process. Further, the method for processing and alerting data in real-time greatly reduces the time it takes to respond to an accident, which is especially important in emergency conditions when every second counts. There is a strong emphasis on data security and privacy in the system's architecture. Passenger privacy is provided by AIDAS's use of modern encryption technologies and data protection procedures, which securely transport and store all acquired data. The system uses MQTT for efficient communications between IoT devices and a central server, facilitating real-time alert production. Emergency response is enhanced by automated alerts sent to first responders and relevant authorities via mobile apps and SMS.

The system's design takes the privacy and security of users' information very seriously, with features like strong access restrictions and checks to make sure data processing follows all applicable laws and ethical guidelines. To improve transit safety and reaction times in the event of an emergency. Public transportation safety has taken a giant leap forward due to the technology, which offers an automatic method for real-time injury identification and alerts. More fast reactions to emergencies, less serious injuries, and lives saved are all possible outcomes of its adoption. AIDAS paves the way for future improvements to public transportation safety throughout the globe by demonstrating how to implement advanced technology to tackle pressing safety issues.

B. IoT Sensors for AIDAS

1) **Accelerometers:** Accidents or injuries may be indicated by these sensors, which record acceleration changes and may detect abrupt stops or collisions.

2) **Sound Sensors:** Unusual sounds or distress signals may be picked up by sound sensors, which add further clues to detect emergency situations.

3) **Pressure Sensors:** In the event of unexpected motion or congestion, pressure sensors may pick up on changes in cabin pressure.

4) **Motion Sensors:** To better monitor passenger movements and spot suspicious patterns of behavior, motion sensors can detect motion within the vehicle.

5) **Temperature Sensors:** A vehicle's temperature sensors may help identify dangerous situations by monitor on the inside temperature.

6) **Proximity Sensors:** One useful feature of proximity sensors is their ability to identify nearby objects or passengers. This allows for easier monitoring of passenger occupancy and the detection of any challenges.

Due to the coordinated efforts of these IoT sensors, the system can monitor the surrounding area of the vehicle in detail, alerting the driver or passengers to any danger as it happens. Choose sensors to precision, reaction speed, durability, compatibility with IoT systems, and capability to function in various environmental situations. Public transportation's AIDAS are system block diagrams shown in Figure 1. The procedure starts with IoT sensors collecting information about the vehicle's dynamics and the passengers' actions, which is then analyzed by a data fusion module. An

onboard CNN analyses the combined data to about the scene of the accident. Event detection initiates alert creation and incident reporting. After reports of incidents, the emergency response & notification system organizes responses.

Enhancing passenger safety in public transportation networks, this integrated strategy allows for real-time injury detection and supports quick emergency responses.

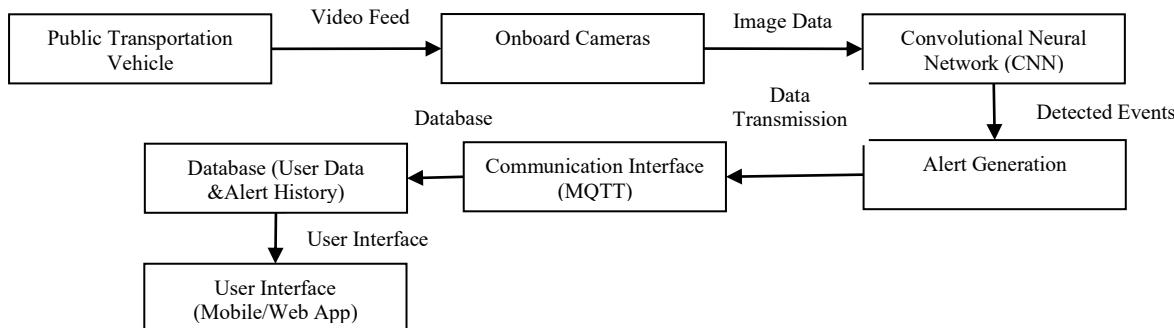


Fig. 1. Block Diagram Proposed AIDAS for Public Transport Safety

The AIDAS system's CNN is shown in Figure 2 as a sequential representation, moving from input data to output predictions. The CNN's feature extraction and incident/injury risk assessment capabilities are enhanced at each stage. Video frames are transformed into image sequences using OpenCV or FFmpeg, which extract frames, resize and normalize them, and save them as image files with consistent file names.

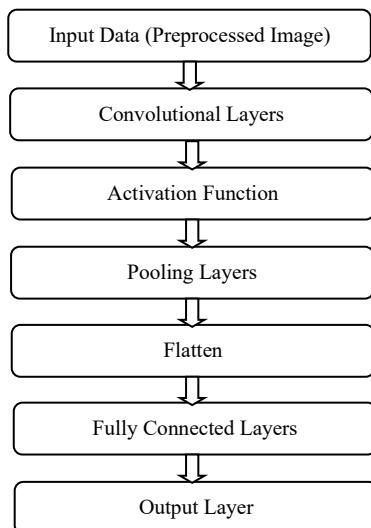


Fig. 2. CNN Flow for AIDAS System

IV. RESULTS AND DISCUSSIONS

AIDAS is a game-changer to public transportation safety standards. By combining IoT devices with CNNs, AIDAS provides a system that can identify any injuries or emergencies among passengers in real-time and send out alerts. Initial results from using AIDAS in trial projects are encouraging. The system's ability to identify and notify authorities of any passenger injuries or distress was impressive. In a flash, AIDAS can spot warning signs like abrupt collisions, strange motions, or distress noises by comparing live video streams from onboard cameras with sensor data from IoT devices.

With AIDAS, public transportation events may be responded to more quickly and with less harm since it

outperforms conventional surveillance systems in both speed and accuracy in both virtual and real-world settings. In addition, by integrating AIDAS with emergency response procedures, reactions to recognized problems may now be coordinated and carried out quickly. The AIDAS system guarantees that the right actions are done quickly by automatically creating comprehensive incident reports and sending them to the necessary parties, such as transportation system operators and emergency response teams.

By improving overall passenger safety and reducing the potential effect of crises inside public transportation networks, this real-time warning technology drastically lowers the time between injury incidence and response. There are significant ethical, privacy, and data security concerns that arise with system development. Data security and protection of passenger privacy are of the utmost importance to AIDAS since the system gathers and processes sensitive information, such as data from sensors and live video feeds. To ensure the privacy of passengers and maintain the system running smoothly, it is necessary to use strong encryption technologies, data anonymization techniques, and stringent access restrictions.

To maintain public faith in the system and ethical norms, it is important to address ethical factors such as openness in data collecting and use, informed consent, and responsibility in decision-making. As important as AIDAS is for the security of public transit, it also has far-reaching consequences for smart city programs and urban mobility. Smart cities have unique problems, but AIDAS shows how the IoT and artificial intelligence (AI) algorithms may conquer these problems. To improve overall resilience and response to unexpected events, similar methods might be modified and used in many areas, such as healthcare, public safety, and infrastructure management. Table 1 displays the sensor data collected by AIDAS from IoT sensors installed in public transportation vehicles.

TABLE I. SENSORY DATA FOR AIDAS SYSTEM IN PUBLIC TRANSPORTATION VEHICLES

Timestamp	Accelerometer	Motion Detected	Pressure (Pa)	Sound Level (dB)	Temperature (°C)	Proximity	Injury Detected	Class Label
2024-03-11 08:00:00	[0.23, -0.12, 0.65]	Yes	101325	68	22.5	0	0	Not Injured
2024-03-11 08:00:05	[0.25, -0.10, 0.62]	No	101320	70	22.7	1	1	Injured
2024-03-11 08:00:10	[0.28, -0.08, 0.60]	Yes	101318	72	22.8	1	0	Not Injured
2024-03-11 08:00:15	[0.30, -0.06, 0.58]	Yes	101310	75	22.9	0	1	Injured
2024-03-11 08:00:20	[0.32, -0.04, 0.55]	No	101305	78	23.0	0	0	Not Injured

The data is recorded with timestamps, and it comprises X, Y, and Z axis combined accelerometer measurements, motion status, pressure readings, sound levels, temperature, proximity information, and injury detection status. With this extensive dataset, the CNN model can instantly examine sensor data, making it easier to spot any passenger ailments or crises. By combining motion and pressure data, the system can better detect problems, leading to better safety measures in public transit. Table 2 shows the image dataset used by AIDAS. Every entry is uniquely identified by an image ID, which is also the filename of the image, and a label that indicates whether the image shows an injury or not. An essential part of AIDAS's CNN model training is this dataset, which allows for precise image-based injury or emergency scenario recognition.

TABLE II. AIDAS IMAGE DATASET

Image ID	Image Filename	Label
1	image001.jpg	Injured
2	image002.jpg	Not Injured
3	image003.jpg	Injured
4	image004.jpg	Injured
5	image004.jpg	Not Injured

Table 3 shows the sizes of the AIDAS CNN dataset. There is an overview of the image counts for the three datasets: training, validation, and testing. To fully grasp how large the dataset was used to train, validate, and test the CNN model within the AIDAS system, this information is essential.

TABLE III. DATASET SIZE OVERVIEW FOR CNN IN AIDAS

Dataset	Size
Training	10,000
Validation	2,500
Testing	2,500

The CNN model's performance across 10 epochs of training is shown in Figure 3. The training accuracy and loss values are shown on the y-axis, while the number of epochs is shown on the x-axis. Since the training accuracy rises from 0.60 to 0.92 during the epochs, it can be inferred that the model's image classification capabilities are gradually enhanced. The training loss drops from 1.5 to 0.2 over time, which means the model is becoming better at reducing mistakes and making accurate predictions. These tendencies are common when the model is learning to match the training data better, which increases accuracy and decreases loss values.

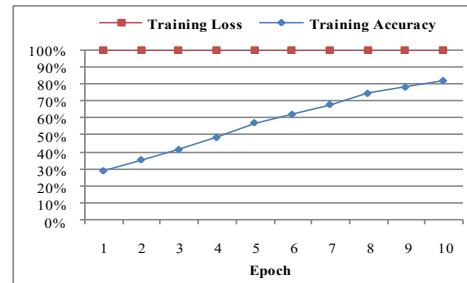


Fig. 3. Training Accuracy and Loss Over 10 Epochs

The CNN model's performance across 10 epochs during validation is shown in Figure 4. Validation accuracy and loss values are shown on the y-axis, with the number of epochs shown on the x-axis. With each passing epoch, the validation accuracy rises from 0.55 to 0.85, showing that the model becomes better at handling unknown input. As the validation loss drops from 1.8 to 0.5, it becomes clear that the model does a good job of minimizing mistakes and generalizing new data. As seen by the growing accuracy and falling loss values during validation, these patterns show that the CNN model does well on both the training data and fresh, unseen data.

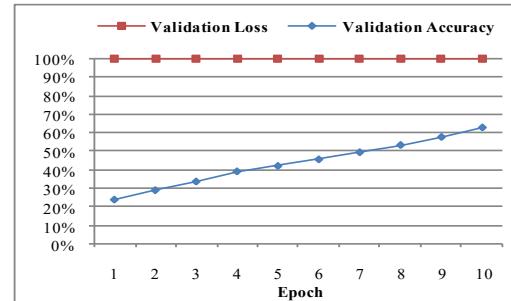


Fig. 4. Validation Accuracy and Loss Over 10 Epochs

The AIDAS uses a CNN and measures its overall performance using several meaningful indicators. It can learn a lot about the model's performance in predicting accidents and injuries in public transportation settings from these indicators. One important indicator is accuracy, which counts how many examples were properly categorized out of all the occurrences. CNN accurately identified 90% of the cases it encountered, as shown by an accurate value of 0.90.

A further crucial parameter is precision, which measures the model's accuracy in identifying positive occurrences (such as wounded passengers) out of all cases defined as positive. In other words, 88% of the cases that the CNN deemed positive were, in fact, positive, according to the accuracy value of 0.88. The sensitivity or recall of a model is its capacity to accurately detect positive cases relative to all real positive instances. A recall rating of 0.92 indicates that 92% of all real positive cases were detected by CNN.

As a fair evaluation of the model's efficacy, the F1-score takes accuracy and recall into account in a harmonic mean. As an example, a well-balanced degree of recall and accuracy is indicated by an F1-score of 0.90. It shows remarkable competence in identifying and handling possible injuries or crises in crowded public transit settings. The AIDAS system's dependability and efficacy in protecting passengers are highlighted by these measures taken as a whole.

The framework's implementation includes Python, TensorFlow/Keras, OpenCV, Flask, MQTT Broker, and SQLite, as well as libraries such as NumPy, Pandas, Matplotlib, Scikit-learn, and PyJWT for different functionality. Enhance performance by optimizing CNN architectures for accelerated processing and using edge computing. Real-time monitoring may be accomplished via the use of effective IoT devices and cloud integration. Generate alerts via threshold-based triggers and notifications. Improve precision by data augmentation, ongoing model training, and the integration of varied datasets for thorough injury identification. Modern encryption methods include AES (Advanced Encryption Standard), RSA (Rivest-Shamir-Adleman), and TLS (Transport Layer Security) for secure data transport. Data protection protocols include access restriction, data anonymization, routine security audits, and automatic backup and recovery systems.

V. CONCLUSIONS

Integrating CNN into AIDAS is a huge step forward in making public transportation systems safer. The CNN model utilizes image data and IoT sensors to efficiently detect possible injuries or emergency scenarios in real-time. IoT sensors, CNN architecture, and data processing methods are all part of this system's integrated solution for injury detection. Due to its capacity to process both visual input and sensor readings, the CNN can reliably identify cases and sound alarms when required. For accurate injury detection with minimal false alarms, the CNN's performance metrics accurately, precision, recall, and F1-score are useful indications. High scores across all these parameters show that CNN can reliably detect and react to emergencies. By using CNN technology, the AIDAS system helps public transportation networks improve operational efficiency, decrease reaction times to problems, and increase passenger safety. The future of injury detection systems based on CNN is bright, and it bodes well for commuters all over the globe.

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