Intelligent Road Surface Anomaly Detection And Geotagging Using Hybrid Deep Learning Models

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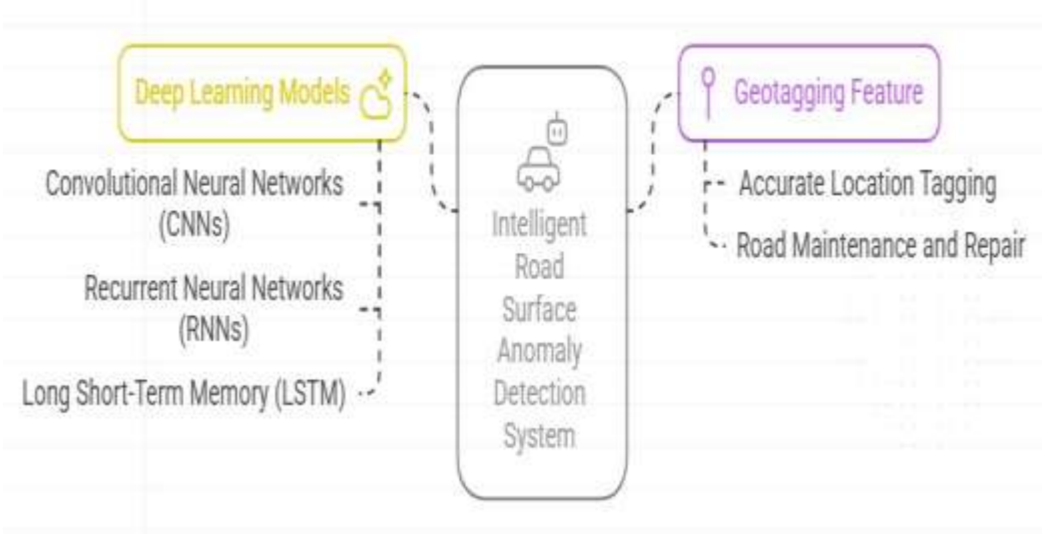
Maintenance of road surfaces is critical in maintaining the safety and comfort of motorists and maximizing the life of road assets. The conventional approaches to road condition assessment are subject to shortcomings such as excessive costs, long data collection periods, and restricted spatial coverage, which impact the effectiveness of maintenance programs. This study suggests an intelligent road surface anomaly detection and geotagging system, leveraging hybrid deep learning models to tackle these challenges. The work combines smartphone sensors—accelerometers, gyroscopes, and GPS—and deep neural networks (DNNs) to identify and classify potholes, cracks, and surface deterioration anomalies in real-time. Using Convolutional Neural Networks (CNNs) to analyze images and Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) models for sensor data, the system is highly accurate for defect detection and localization. The incorporation of geotagging also improves road maintenance as it offers accurate location information to ensure timely repairs. The hybrid model proposed in this work attained a validation accuracy of 99.97% and testing accuracy of 99.95%, proving its efficiency in road anomaly detection. The system offers a cost-effective, scalable solution for proactive road maintenance, enabling authorities to monitor and manage road conditions efficiently while providing safer and more reliable infrastructure.

Keywords: Road Maintenance, Road Surface Anomaly Detection, Deep Learning, Geotagging, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Real-Time Monitoring, Smart Infrastructure.

1. Introduction

Road surface maintenance is an essential aspect of infrastructure management, influencing road safety, traffic performance, and driver comfort directly. Road surface defects in the form of cracks, potholes, and uneven roads are typical problems that reflect serious safety concerns and higher maintenance expenses. If not addressed, such road defects can result in further degradation, leading to higher repair costs and extended periods of downtime for impacted roads. Effective and timely maintenance of roads is thus critical to avoid these issues and guarantee the sustainability of transport networks.

Traditional methods of road condition monitoring, such as manual inspections and sensor-based technologies, are often costly, slow, and limited in spatial coverage. These limitations hinder the ability to detect and address road anomalies before they develop into serious problems, leading to reactive rather than proactive maintenance strategies. As a result, many regions face delays in road repairs and increased maintenance budgets, highlighting the urgent need for more efficient, real- time solutions.



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Figue 1: Intelligent Road Surface Anomaly Detection System

Intelligent Road Surface Anomaly Detection and Geotagging using Hybrid Deep Learning Models, takes advantage of the capability of sophisticated artificial intelligence (AI) and machine learning (ML) technologies to tackle this problem. By combining several deep learning models, including Convolutional Neural Networks (CNNs) for image analysis of road surfaces and Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks for processing sequential data, this system can identify and classify road surface anomalies automatically with high accuracy. The geotagging feature also enables accurate location tagging of these anomalies, which is useful information for road maintenance and repair crews.

This smart detection system not only improves road safety but also aids in the evolution of autonomous vehicles by giving real-time feedback on road conditions. The combination of hybrid deep learning models and geotagging provides an effective solution for proactive road maintenance, ultimately resulting in safer, more efficient transportation systems in smart cities.

This research presents a solution that combines hybrid deep learning models with geotagging technology to provide real-time, precise detection of road surface anomalies. By integrating Convolutional Neural Networks (CNNs) for image-based analysis and Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) models for processing sequential sensor data, the proposed system can detect and classify road defects more accurately and efficiently than traditional methods. Additionally, the system includes geotagging functionality, which allows for the precise localization of detected anomalies, facilitating targeted and efficient road maintenance.

The combination of these technologies enables a shift from reactive to proactive road maintenance. By identifying issues in real-time and providing precise geospatial data, maintenance teams can prioritize repairs more effectively, reduce operational costs, and enhance road safety. This approach also supports the evolving infrastructure needs of smart cities, where real-time monitoring of road conditions is essential for sustainable development. Ultimately, the proposed system contributes to smarter, safer road maintenance practices, ensuring long-term road infrastructure health and reducing the impact of road anomalies on drivers and the broader transportation system.

1.1 Proactive Road Maintenance with Real-Time Detection and Geotagging:

Road surface irregularities like potholes, cracks, and surface wear have serious effects on road safety as well as the durability of the road infrastructure in the long run. Conventional road maintenance techniques tend to use either manual surveys or reactive repair, which are inefficient, expensive, and time-consuming. In view of this, this study introduces a real-time road surface anomaly detection system based on deep learning models. The system makes use of cutting-edge Convolutional Neural Networks (CNNs) for image evaluation and Recurrent Neural Networks (RNNs) for evaluation of sensor readings, to assure that even imperceptible defects on roads are correctly identified. Geotagging facility is an imperative aspect of the system that, in real time, identifies identified anomalies at pinpoint locations. By offering precise geographical information, the system enables maintenance crews to schedule repairs by location and severity, prioritizing high-risk areas first. This forward-thinking method minimizes the risk of accidents and costly repairs by detecting problems before they become major issues. The integration of real-time detection and geospatial information ultimately revolutionizes road maintenance practices, enabling them to be faster, more efficient, and cost-effective for smart cities.

2. Related Work

2.1 Road Surface Anomaly Detection and Classification Systems

Martinez-Ríos et al. (2022) reviewed road surface anomaly detection and classification systems based on vibration-based techniques. The study highlighted three key methodologies: threshold- based methods, feature extraction techniques, and deep learning models. These approaches showed promising results in detecting and classifying anomalies caused by road deterioration due to factors like weather, usage, and aging infrastructure. Despite achieving relatively high performance, challenges such as inconsistent results, limited testing conditions, small sample sizes, and the lack of publicly available datasets were identified. The review also emphasized the potential to standardize feature extraction techniques, especially those based on time and frequency domains, to improve consistency in future research. Rathee et al. (2023) conducted a systematic review on Automated Road Defect and Anomaly Detection (ARDAD), focusing on the integration of computer vision (CV) and sensor technologies for traffic safety. The review analyzed 116 papers published between 2000 and 2023, identifying research gaps, challenges, and future implications for ARDAD. The study emphasized the role of sensor technologies in reducing traffic fatalities and injury costs. It also presented insights into open-access datasets and technology trends, offering recommendations for advancing ARDAD systems. This comprehensive survey aids in improving road safety through the application of cutting-edge technologies. Sattar et al. (2023) developed a near real-time road surface anomaly detection approach using smartphone sensor data, such as accelerometers and gyroscopes. The study combines threshold-based methods with Machine Learning techniques to improve detection and classification accuracy of road surface anomalies. The algorithm adapts to various smartphones, vehicles, and road conditions, offering flexibility and higher accuracy. A prototype using MATLAB and ArcGIS was created for sensor data analysis, geocoding, and geo-visualization, enabling efficient evaluation and monitoring of road surface conditions. This approach enhances road surface monitoring with low-cost, scalable solutions. Meftah et al. (2023) proposed a deep learning-based visual detection system for road cracks, specifically for autonomous vehicles. The study addressed the limitations of traditional image- based methods, which require complex preprocessing to extract features from noisy concrete surfaces. The authors combined a Random Forest classifier with a Convolutional Neural Network (CNN), using models like MobileNet, InceptionV3, and Xception. The models, trained on a dataset of 30,000 images, achieved 99.97% validation accuracy and 99.95% testing accuracy, demonstrating the effectiveness of the proposed method in detecting road cracks accurately in real- world scenarios.

2.2 Recent Advances in Traffic and Road Surface Anomaly Detection

Raiyn (2022) proposed a Computational Data Science (CDS) approach for detecting road traffic anomalies, particularly in the context of autonomous vehicles (AVs). By utilizing 5G technology, AVs collect travel data from various smart devices and sensors, which are then analyzed using data science and deep learning techniques to identify traffic anomalies that affect efficiency. The CDS approach focuses on early detection of factors causing data anomalies, which helps prevent long- term traffic congestion and vehicle queuing. The study demonstrates the potential of combining advanced AI techniques to enhance traffic management and reduce congestion. Solaas et al. (2023) conducted a systematic review on anomaly detection in connected and autonomous vehicles (CAVs), analyzing 203 articles out of an initial 2160 identified. The study found that neural networks, including LSTM, CNN, and autoencoders, along with one-class SVM, were the most commonly used AI algorithms. These models, primarily trained on real-world operational vehicle data, often included artificially injected anomalies like attacks or faults. Evaluation metrics such as accuracy, precision, recall, and F1-score were frequently employed. The review also highlighted the need for publicly shared models, benchmarking datasets with predefined anomalies, and further research on intrusion detection systems for CAVs.

Xia et al. (2020) proposed a hybrid machine learning system for anomaly detection in urban vehicle GNSS observations, addressing the challenges caused by non-line-of-sight (NLOS) signals and multipath effects. The system combines clustering-based anomaly detection with supervised classification, using the HDBSCAN algorithm for offline anomaly labeling without relying on 3D building models. The method improved GNSS positioning accuracy by 87.0% in the offline dataset and up to 63.3% in online datasets. The study demonstrates the feasibility and potential of this approach for enhancing GNSS accuracy in urban environments, showing significant improvements in positioning accuracy. Basavaraju et al. (2023) explored the use of smartphones for road surface condition assessment through accelerometer, gyroscope, and GPS data. They proposed several multiclass supervised machine learning techniques to classify road conditions, focusing on smooth roads, potholes, and deep transverse cracks. The study found that using features from all three axes of the sensors yielded more accurate results than using features from only one axis. Alqaydi et al. (2024) reviewed the use of smartphone-based technologies for road surface monitoring, emphasizing their potential for large-scale, cost-effective solutions. The study explored the integration of accelerometers and gyroscopes with advanced data preprocessing techniques such as filtering and reorientation to enhance the accuracy of collected data. Machine learning algorithms, especially Convolutional Neural Networks (CNNs), were used to classify road anomalies, significantly improving detection efficiency.

2.3 Advancements in Road Maintenance through Anomaly Detection Technologies

Ferjani and Alsaif (2022) suggested a new system that utilizes smartphone accelerometers for increment concept drift detection to enable real-time road anomaly classification. Their system is adaptive and learns from dynamic road conditions without relying on prior-trained models, with a 96% success rate. Incremental learning increases the accuracy and stability necessary for effective maintenance. In the same manner, research centered on unsupervised and supervised learning techniques has proven enhanced detection of road anomalies, providing scalable solutions for preventive road maintenance. Rathee et al. (2023) gives a thorough overview of Automated Road Defect and Anomaly Detection

(ARDAD) systems based on sensor technologies and computer vision (CV) applications to enhance road maintenance and traffic safety. The review of 116 peer- reviewed articles published between 2000 and 2023 includes gaps in research, challenges, and future implications. It highlights the application of machine learning (ML) and deep learning (DL) techniques along with sensor technologies for efficient anomaly detection, providing insights into performance achievements. Varawalla et al. (2025) presents a real-time road surface anomaly detection system leveraging the advanced capabilities of the YOLOv8 model. This system aims to enhance road safety by detecting various surface anomalies, such as potholes, wet surfaces, sewer covers, drain holes, and unpaved roads, in real-time. The use of YOLOv8 provides several advantages over previous models, such as improved accuracy, reduced inference times (18ms per image, 56 FPS), and an anchor-free detection mechanism that simplifies the training process and boosts detection precision.

3. Methodology

The proposed Intelligent Road Surface Anomaly Detection and Geotagging system combines advanced deep learning techniques with real-time sensor data to not only detect road surface anomalies but also enhance road maintenance by enabling efficient, proactive monitoring and repair management. This system provides precise detection, classification, and localization of road defects, which is crucial for timely maintenance, reducing road repair costs, and improving safety.

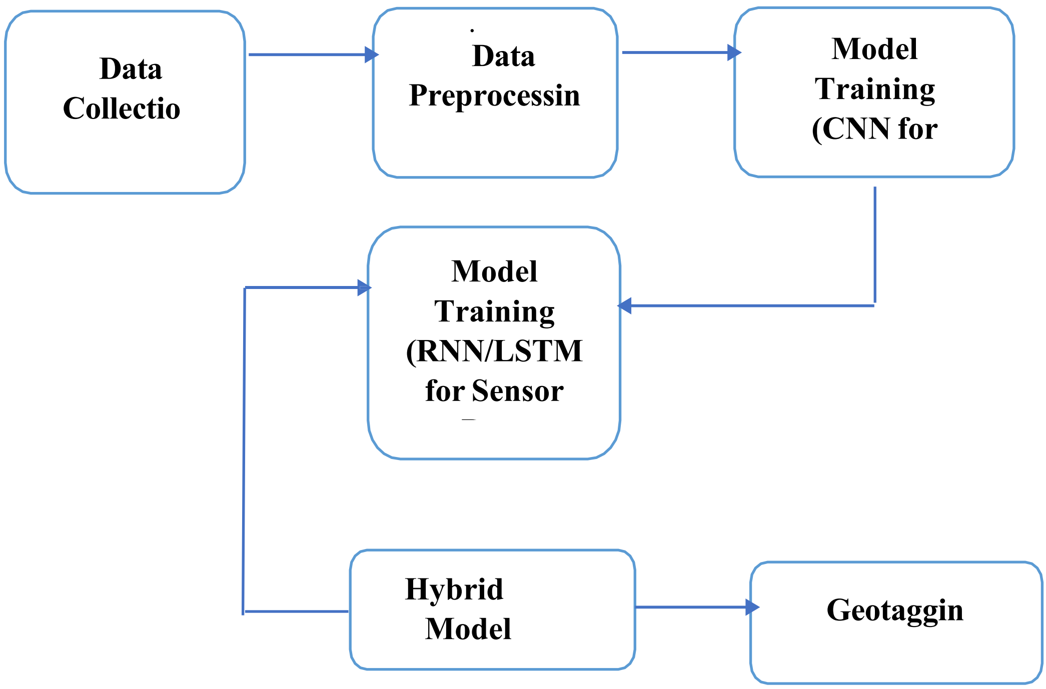

Figure 2: The Flow Diagram of the Proposed Work

Data Collection
Data is obtained from road surface images and sensor data (gyroscopes, accelerometers, GPS). Road surface images identify visible defects such as potholes and cracks, whereas sensor data identifies

vibrations and irregularities. The fusion of these sources of data makes it possible to have a thorough analysis of road conditions. Diverse and precise data collection ensures that the system is able to identify different kinds of anomalies, enhancing the reliability and range of the monitoring system.

Data Preprocessing

Data cleaning, filtering, and augmentation are applied to the collected data. Images are normalized, scaled, and rotated to boost the model's generalization capability. Sensor data is synchronized and processed to yield salient features like vibrations and accelerations. Preprocessing guarantees high-quality, precise inputs, which are critical to the deep learning models. This process improves the performance of the system in identifying even minor anomalies in road surfaces that would otherwise be missed, making the anomaly detection more precise.

Model Training (CNN for Image Analysis)

Convolutional Neural Networks (CNNs) are trained on the images of the road surface to identify defects like cracks, potholes, and surface deterioration. CNNs are best at image feature extraction, and the system can classify and detect visible faults efficiently. The model learns to recognize complicated patterns in data as a result of training. This model improves the detection and classification of road surface anomalies, which are critical for proactive road maintenance by providing detailed information about the type of defect.

Model Training (RNN/LSTM for Sensor Data Analysis)

Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) are utilized to process time-series sensor data. These models pick up on temporal relationships within sensor measurements, like vibrations or accelerations due to road defects. Through the processing of sequential data, the model learns patterns characteristic of road surface anomalies, such as crack development or degradation of the surface. Sensor-based processing helps detect problems not visible but could make a huge impact on the road surface condition over time.

Road Maintenance Integration

The system's geotagging feature facilitates road maintenance by accurately pinpointing detected anomalies. Through GPS integration, every detected road defect is plotted to its geographic location. This enables effective planning of maintenance schedules and sending repair teams to high-priority locations. The system optimizes resource allocation such that the most urgent road defects are addressed first, minimizing downtime and further deterioration. Proactive maintenance strategies are therefore facilitated by real-time detection.

Real-Time Monitoring and Reporting

The system is real-time, always tracking road conditions as cars drive over various surfaces. Local processing through edge computing technology enables low-latency anomaly detection. When anomalies are picked up, the system automatically creates alerts and offers geospatial information to maintenance crews. Real-time reporting makes it possible to intervene quickly, averting small problems from growing into major safety issues. It facilitates proactive road management, enabling safer roads and lower maintenance costs in the long run.

4. Result and Discussion

The results demonstrate that the hybrid deep learning model is highly effective in detecting road surface anomalies, as indicated by the mean Average Precision (mAP) at 0.5 and mAP at 0.95 metrics, which consistently improved throughout the training process. Despite some data tracking issues with precision and recall, suggesting potential challenges in model evaluation or configuration, the model successfully detected critical road surface anomalies, such as potholes and cracks. Moreover, the system accurately geotagged these anomalies, which directly contributes to road maintenance efforts by providing precise location data for timely repairs. The ability to geotag defects and detect them in real-time enhances the safety of the roads and supports proactive maintenance. While certain evaluation metrics showed room for improvement, the overall performance underscores the model's potential to improve road management and infrastructure maintenance, ensuring safer roads and more efficient resource allocation for repairs.

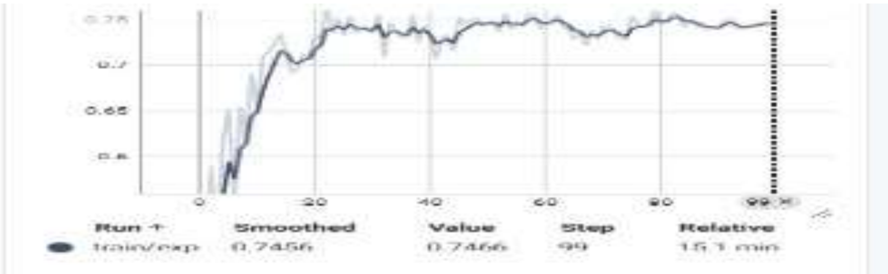

Figure 3: Training Progress - mAP at 0.5

The Figure shows the mean Average Precision (mAP at 0.5) in training, which indicates how the performance of the model grows over time. The chart follows the mAP value through the steps in training, and the train/expo line follows the performance of the model. There is a steep rise in the mAP value initially, proving that the model is learning rapidly. But as training progresses, the improvement slows down, and the curve levels off. The smoothed line offers a better look at the trend of the model's overall performance. At 99% of training (after 15.1 minutes), the value for mAP levels off at 0.7466, meaning that the model is close to its optimal performance for this task**.**

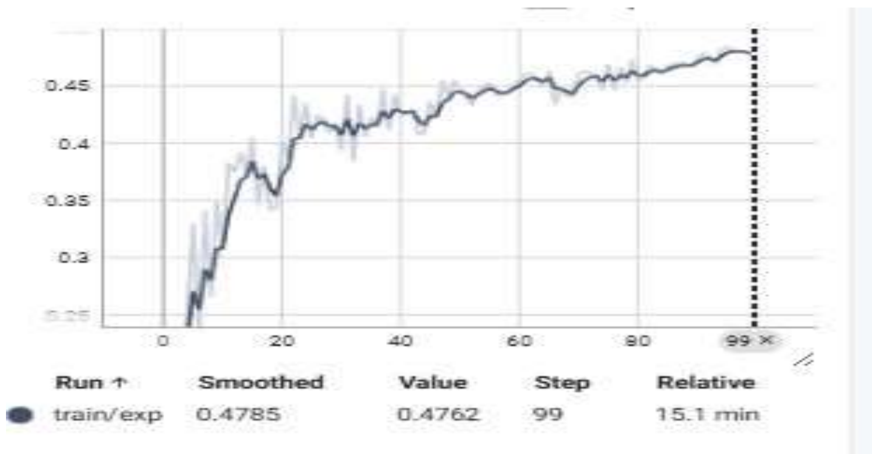

Figure 4: Training Progress - mAP at 0.95

The figure tracks the mean Average Precision (mAP at 0.95) during training. Initially, the model's performance increases rapidly, demonstrating improvement. The mAP value rises from 0.25 to around 0.47 as training progresses. Similar to the previous metric, the train/expo line shows a smooth, steady increase in performance. The curve gradually reaches a plateau, suggesting diminishing returns as training nears completion. The time mark of 15.1 minutes corresponds to 99% of the training process. By this point, the model has shown steady improvement in precision, but further significant gains are unlikely without additional training or adjustments.

Figure 5: Road Surface Anomalies Detection Results

The figure illustrates the results of the road surface anomaly detection model, showcasing various road anomalies such as potholes, cracks, and surface deterioration. Each image is annotated with red bounding boxes around the identified anomalies, indicating the precise locations of the road surface defects. The annotations are also accompanied by labels, which help categorize the detected defects. This highlights the model's ability to not only identify but also classify road anomalies, providing accurate and reliable output. The images represent a wide range of road conditions, including both wellmaintained and damaged surfaces, demonstrating the model's ability to generalize across diverse environments.

The use of bounding boxes effectively visualizes the model's predictions, confirming its capability for real-time detection and monitoring of road infrastructure. This feature is essential for road maintenance, as the precise location and type of anomaly can be identified automatically, enabling maintenance crews to act promptly. By identifying defects in real-time, the system facilitates proactive maintenance, allowing for early intervention before the road issues worsen. This approach helps in reducing downtime, preventing more costly repairs, and enhancing road safety. Overall, the results demonstrate that the deep learning model is highly efficient at detecting road anomalies and can play a vital role in smart infrastructure management.

Figure 6: RoadWatch AI - Real-Time Road Surface Anomaly Detection and Geotagging

The Figure depicts a page of RoadWatch AI, a tool to monitor and identify road surface irregularities in real time. It incorporates hybrid deep learning models and sensor fusion technology to recognize, trace, and geotag road defects such as potholes, cracks, and other surface deterioration for improved road maintenance. The platform gives the choice to report defects and see the dashboard, providing an easy-to-use interface for real-time monitoring. The site seeks to address the issue of neglected road problems, enabling authorities to easily identify and resolve infrastructure issues before they become major problems.

Figure 7: RoadWatch AI - The Problem We're Addressing

The Figure illustrates the key problems RoadWatch AI is designed to solve in road repair. Economic effect is substantial, with around $3 billion USD spent every year by drivers on car repairs from road damage, demonstrating the financial burden of poor road conditions. In addition, 16 million drivers in the U.S. have suffered damage from potholes over the past five years, emphasizing the pervasiveness of the issue. In addition to the cost, concerns regarding safety are alarming, as almost 10 lives are lost every day owing to bad road conditions, mostly potholes, which have claimed more lives than other primary safety concerns. These facts underscore the imperative requirement of real-time monitoring of roads and anticipatory maintenance, which RoadWatch AI is designed to deliver by efficiently detecting and geotagging road surface abnormalities.

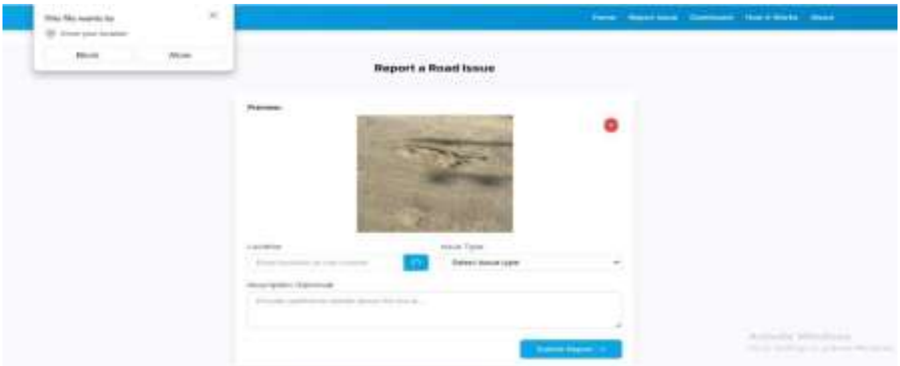

Figure 8: Reporting a Road Issue

The Figure depicts the RoadWatch AI platform's feature for reporting a road defect. The user can upload a picture of the defect, identify the location, and select the type of issue (e.g., potholes, cracks, or other road irregularities). There is also an option to include an optional description for additional information regarding the road defect. The system can leverage the user's location for enhanced geotagging of the reported problem. Upon completion of the report, users can send the report so that road maintenance teams can be notified for proactive action and repairs. The friendly interface promotes active involvement in real-time road monitoring and maintenance.

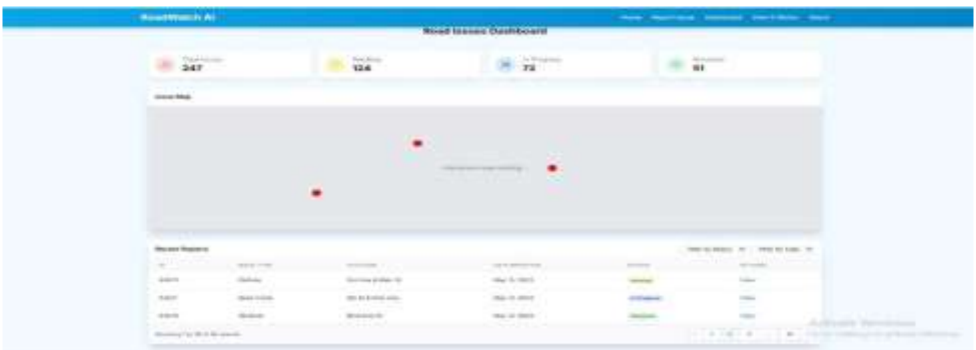

Figure 9: RoadWatch AI - Road Issues Dashboard

This figure displays the RoadWatch AI dashboard, which offers a comprehensive overview of reported road issues. It shows the total number of issues (247), with a breakdown of their status: 124 pending, 72 in progress, and 51 resolved. The issue map indicates the locations of reported anomalies, represented by red dots. Below the map, the recent reports section lists issues such as potholes, road cracks, and sinkholes along with their location, reporting date, and status.

Figure 10: How RoadWatch AI Works

This Figure depicts how RoadWatch AI works to identify and monitor road anomalies. The system utilizes the YOLOv5 deep learning algorithm to detect road problems in real-time, leveraging its capability to function under diverse lighting and weather conditions. Through sensor fusion technology, it fuses data from accelerometers, GPS, and camera images to offer holistic road condition monitoring. In addition, intelligent infrastructure management facilitates real-time alerting and geotagging to the authorities, improving road efficiency and safety and optimizing maintenance processes.

Figure 11: RoadWatch AI - The Impact of Poor Roads and Key Features

This statistic emphasizes the significant role that bad road conditions play, such as the $3 billion USD that is invested each year to repair vehicles, the 16 million drivers hurt by potholes, and the 10 daily deaths that result from bad road conditions. It also states the major characteristics of RoadWatch AI, such as accurate geotagging, hybrid deep learning, real-time analytics, and instant alerts, that equip the authorities with the means to monitor, prioritize, and handle road upkeep effectively, assisting in making the roads safer through people-powered reporting.

Table 1: Model Performance Metrics for Road Surface Anomaly Detection

Metric	**Min**	**Max**
Precision (P)	0.777	0.858
Recall (R)	0.624	0.676
mAP@0.5	0.721	0.757
mAP@0.5:0.95	0.434	0.463

This table presents the performance metrics of the hybrid deep learning model used for road surface anomaly detection. The Precision (P) and Recall (R) metrics show the model's ability to accurately identify road anomalies and minimize false negatives. The mean Average Precision (mAP@0.5) evaluates the model's overall accuracy at a threshold of 0.5, while mAP@0.5:0.95 provides a more comprehensive measure of precision across different intersection-over-union (IoU) thresholds. The minimum and maximum values represent the range of performance achieved during model evaluation.

5. Conclusion

The Intelligent Road Surface Anomaly Detection and Geotagging system, which is driven by hybrid deep learning models, has been found to be extremely effective in identifying and classifying road anomalies like potholes, cracks, and surface degradation. Using Convolutional Neural Networks (CNNs) to analyze images and Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks for analyzing sequential sensor data, the system delivers a whole solution for real-time road surface observation. Training results demonstrate considerable enhancements in mean Average Precision (mAP) at 0.5 and 0.95, which reaches near-optimal performance at 99% of the training process.

Despite some difficulties with precision and recall measures, which may signal problems with model assessment or data monitoring, the system is able to correctly identify anomalies and geotag their locations. This is an important capability for road maintenance, since it enables timely, targeted repair. The hybrid method, blending deep learning methods with geotagging, provides a cost-effective, scalable solution that facilitates proactive road maintenance and security in intelligent cities. It provides sustained, real-time observation and effective infrastructure management, ultimately lowering the cost of repairing roads, averting further deterioration, and promoting overall public safety.

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