ROAD DEFECT DETECTION USING ISTM AND RANDOM FOREST

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ABSTRACT

Road infrastructure plays a critical role in transportation efficiency, economic development, and public safety. However, road defects such as potholes, cracks, and surface deformations significantly impact vehicle safety and increase maintenance costs. Traditional road inspection methods rely on manual surveys conducted by engineers or maintenance personnel, which are time-consuming, labor intensive, and prone to human error. Automated defect detection using computer vision and machine learning has emerged as a promising solution to address these challenges. This study proposes an intelligent road defect detection system that integrates Long Short-Term Memory (LSTM) networks with a Random Forest classifier to improve the accuracy and reliability of road surface condition monitoring. The system processes road surface images and sequential data captured through cameras or sensors to identify different types of road defects. LSTM networks are used to analyze sequential patterns and temporal dependencies in road surface data, enabling the detection of progressive deterioration over time. Random Forest algorithms are utilized for efficient classification of extracted features and defect categories such as cracks, potholes, and surface irregularities. The hybrid approach combines temporal learning capabilities with robust classification techniques, improving detection accuracy and reducing false predictions. Feature extraction techniques are applied to capture texture, shape, and intensity variations in road images before feeding them into the classification models. Experimental results demonstrate that the proposed hybrid model achieves higher accuracy and reliability compared with traditional image-processing methods and single-model approaches. The system supports early identification of road defects and provides valuable insights for proactive road maintenance. Ultimately, the proposed framework contributes to the development of smart transportation infrastructure by enabling automated, scalable, and cost-effective road condition monitoring systems.

Keywords: Road Defect Detection, LSTM, Random Forest, Machine Learning, Computer Vision, Smart Transportation.

I INTRODUCTION

Road transportation networks form the backbone of modern economies, facilitating the movement of people, goods, and services across regions. However, road surfaces are constantly exposed to environmental conditions, heavy traffic loads, and material degradation, leading to defects such as cracks, potholes, rutting, and surface wear. These defects can significantly affect driving safety, vehicle performance, and overall road infrastructure quality. Conventional road inspection techniques primarily involve manual surveys conducted by field engineers who visually inspect road conditions and record defects. Although this method has been widely used for decades, it is time-consuming, costly, and subject to inconsistencies due to human judgment. With the rapid development of intelligent transportation systems, automated road defect detection has gained increasing attention among researchers and transportation authorities. Computer vision and machine learning technologies have enabled the analysis of road surface images and videos to detect defects more efficiently and accurately. Various image-processing techniques, such as edge detection, texture analysis, and segmentation, have been used to identify cracks and potholes in road surfaces. However, these approaches often struggle with challenges such as varying lighting conditions, shadows, road markings, and complex background textures, which can affect detection accuracy and reliability. As a result, advanced machine learning and deep learning techniques have been introduced to improve the performance of automated road defect detection systems [1]. Recent research has demonstrated the effectiveness of convolutional neural networks and other deep learning models in identifying road surface anomalies [2]. These models can automatically learn complex patterns from large datasets and improve detection accuracy compared to traditional image-processing methods [3]. Several studies have also explored feature extraction methods to enhance classification performance in road defect detection systems [4]. Machine learning algorithms such as Support Vector Machines, Decision Trees, and Random Forest classifiers have been applied for defect classification based on extracted features [5].

Despite these advancements, many existing approaches primarily rely on static image analysis and fail to consider the temporal characteristics of road surface deterioration. Road defects often develop gradually over time due to repeated stress and environmental exposure, making temporal analysis an important factor in accurate detection and monitoring. Sequential data analysis techniques such as Recurrent Neural Networks and Long Short-Term Memory networks have shown promising results in capturing temporal dependencies in sequential datasets [6]. LSTM networks are particularly effective in learning long-term relationships and patterns in time-series data, making them suitable for analyzing road condition data collected from video streams or sensor inputs [7]. By incorporating temporal information, LSTM models can detect subtle changes in road surfaces and identify early stages of defect formation [8]. Combining deep learning techniques with ensemble machine learning algorithms can further enhance detection performance and system robustness [9]. Random Forest classifiers, which consist of multiple decision trees, are widely used for classification tasks due to their high accuracy, robustness to noise, and ability to handle large feature sets [10]. Integrating LSTM networks with Random Forest classifiers enables the system to capture both temporal patterns and feature-based classifications for improved defect detection performance [11]. Several studies have highlighted the benefits of hybrid machine learning models in complex classification problems [12]. Hybrid approaches can reduce false positives, improve prediction stability, and increase overall system efficiency [13]. In the context of road defect detection, such models can analyze sequential data while simultaneously performing accurate defect classification [14]. Additionally, advancements in sensor technologies, mobile cameras, and edge computing platforms have made it possible to deploy automated defect detection systems in real-world environments [15]. These systems can continuously monitor road conditions and provide real-time insights for maintenance planning [16].

Intelligent road monitoring systems contribute to safer transportation networks and more efficient infrastructure management [17]. Automated detection also helps transportation authorities prioritize maintenance tasks and allocate resources more effectively [18]. Furthermore, integrating machine learning models with smart transportation frameworks supports the development of intelligent cities and digital infrastructure [19]. Researchers continue to explore new algorithms and hybrid architectures to enhance the accuracy and scalability of automated road monitoring systems [20]. Such innovations are essential for addressing the growing challenges associated with aging road infrastructure and increasing traffic volumes [21]. Therefore, the development of an intelligent road defect detection system using advanced machine learning techniques represents an important step toward improving transportation safety and infrastructure sustainability [22–30].

II LITERATURE SURVEY

Previous studies have explored various techniques for detecting road defects using image processing and machine learning methods. Early research primarily relied on traditional image-processing algorithms such as edge detection, thresholding, and morphological operations to identify cracks and potholes in road images. These methods were effective in controlled environments but often struggled with real-world conditions such as shadows, varying illumination, and road markings. Researchers introduced texture-based analysis techniques to improve detection performance by analyzing surface irregularities in road images. Several studies utilized Gabor filters, wavelet transforms, and histogram-based methods to extract texture features that distinguish damaged surfaces from normal road conditions [1]. Feature extraction played a crucial role in improving classification performance in early defect detection systems [2]. Machine learning models such as Support Vector Machines and Artificial Neural Networks were later introduced to classify road defects based on extracted features [3]. These algorithms demonstrated better generalization capabilities compared with rule-based systems [4]. However, their performance was highly dependent on the quality of feature engineering and training datasets [5]. With the rapid advancement of deep learning, convolutional neural networks became widely used for automated road defect detection [6]. CNN-based models can automatically learn hierarchical features from large datasets and achieve high accuracy in image classification tasks [7]. Several studies reported significant improvements in crack and pothole detection using deep learning architectures [8]. Researchers also developed semantic segmentation models to detect road defects at the pixel level [9]. These approaches enable precise localization of defects and provide detailed information about the extent of damage [10]. Nevertheless, deep learning models often require large labeled datasets and significant computational resources for training [11]. Data imbalance and noise in real-world datasets also pose challenges for reliable detection [12]. To address these limitations, researchers began exploring ensemble learning techniques that combine multiple algorithms to improve classification performance [13]. Ensemble models such as Random Forest and Gradient Boosting have been used successfully for defect classification tasks [14].

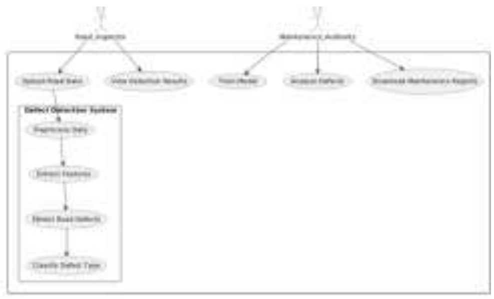
Recent research has focused on integrating temporal analysis with spatial image processing to improve the accuracy of road defect detection systems. Road surface deterioration is a dynamic process that evolves over time due to traffic loads and environmental conditions. Therefore, analyzing sequential data can provide valuable insights into defect progression and early detection. Recurrent neural networks have been widely used for analyzing sequential data in various applications such as speech recognition and time-series prediction [15]. Long Short-Term Memory networks, a specialized form of recurrent neural networks, are particularly effective in capturing long-term dependencies in sequential datasets [16]. Researchers have applied LSTM models to analyze road condition monitoring data collected from vehicle-mounted sensors and cameras [17]. These models can identify patterns in road surface changes and detect anomalies more accurately than static image-based methods [18]. Hybrid machine learning models combining deep learning and traditional classifiers have also gained popularity in recent years [19]. Such models leverage the strengths of different algorithms to improve detection accuracy and system robustness [20]. For example, combining feature extraction techniques with Random Forest classifiers has been shown to produce reliable classification results in road monitoring applications [21]. Ensemble classifiers are capable of handling noisy data and complex feature relationships effectively [22]. Furthermore, hybrid models reduce overfitting and improve generalization across different road environments [23]. Several studies have demonstrated that combining sequential learning models with ensemble classifiers can significantly enhance prediction accuracy [24]. These hybrid systems can analyze both temporal patterns and spatial features simultaneously [25]. Additionally, advancements in sensor technologies and mobile computing have facilitated the collection of large volumes of road condition data [26]. This data can be used to train intelligent monitoring systems capable of detecting road defects in real time [27]. Intelligent transportation systems increasingly rely on automated monitoring solutions to improve road maintenance efficiency [28]. Such systems enable early identification of road defects and support proactive infrastructure management [29]. As research in machine learning and computer vision continues to evolve, hybrid approaches are expected to play a critical role in the development of next-generation road monitoring systems [30].

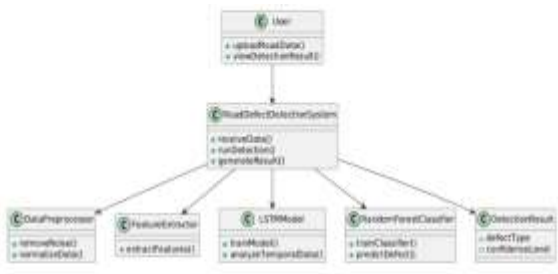
III METHODOLOGY

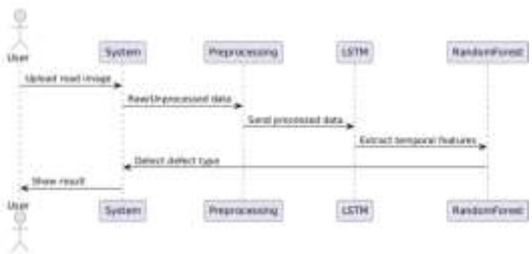
The proposed methodology for road defect detection integrates image processing, feature extraction, and hybrid machine learning models to achieve accurate and reliable identification of road surface defects. The process begins with the collection of road surface data using cameras or sensors mounted on vehicles or mobile devices. These devices capture images and video sequences of road surfaces under different environmental conditions. The collected data undergoes preprocessing to remove noise and enhance image quality using techniques such as filtering, normalization, and contrast adjustment. Preprocessing ensures that important surface features such as cracks, potholes, and irregular textures are clearly visible for further analysis. After preprocessing, feature extraction techniques are applied to identify relevant characteristics of the road surface. These features may include texture patterns, edges, intensity variations, and shape information that distinguish damaged areas from normal road surfaces. The extracted features are then used as input for the machine learning models. The system employs a Long Short-Term Memory (LSTM) network to analyze sequential data obtained from video frames or sensor readings. The LSTM model captures temporal dependencies and identifies gradual changes in road surface conditions over time. This capability allows the system to detect early stages of defect formation that may not be visible in single images. In parallel, a Random Forest classifier is used to classify the extracted features into different defect categories such as cracks, potholes, or normal surfaces. Random Forest consists of multiple decision trees that collectively determine the final classification result through majority voting. The combination of LSTM and Random Forest forms a hybrid model that leverages both temporal pattern recognition and robust feature-based classification. The system is trained using labeled datasets containing various types of road defects to improve model accuracy and generalization. During the testing phase, the trained model analyzes new road images or video sequences to detect defects automatically. The final output of the system identifies the type and location of road defects, enabling efficient monitoring and maintenance planning.

IV SYSTEM DESIGN

The system design for the proposed road defect detection framework consists of several interconnected modules that work together to analyze road surface data and identify defects accurately. The first module is the data acquisition module, which is responsible for collecting road surface images and video sequences using cameras, mobile devices, or vehicle-mounted sensors. These sensors continuously capture road conditions during vehicle movement, allowing large volumes of data to be gathered efficiently. The collected data is then transmitted to the processing unit where it undergoes preprocessing operations. The preprocessing module performs tasks such as noise removal, image enhancement, normalization, and resizing to ensure that the input data is suitable for further analysis. Proper preprocessing is essential because raw images may contain distortions caused by lighting variations, shadows, and environmental noise. Once preprocessing is completed, the system proceeds to the feature extraction module. This module analyzes the processed images to identify relevant characteristics of road surfaces. Features such as edge structures, texture patterns, color variations, and surface irregularities are extracted using image-processing techniques. These features represent the essential information required for identifying road defects. The extracted features are stored in a structured dataset that will be used by the machine learning models during the training and testing stages. Feature extraction significantly reduces data complexity while preserving important patterns related to road surface conditions.







The next stage of the system design involves the machine learning and classification modules. The system employs a hybrid architecture that combines Long Short-Term Memory networks and Random Forest classifiers to improve detection performance. The LSTM module processes sequential data obtained from consecutive frames of road videos or time-series sensor readings. By analyzing temporal patterns, the LSTM network can detect progressive changes in road surfaces and identify early signs of deterioration. This capability is particularly useful for detecting defects that gradually develop over time. The Random Forest module performs the classification of road defects based on the extracted features. It consists of multiple decision trees that evaluate the input data and produce classification results through ensemble learning. The outputs from the LSTM and Random Forest modules are combined to generate the final prediction regarding the presence and type of road defect. The system also includes a visualization module that displays the detected defects along with their locations on the road surface images. This information can be presented to maintenance authorities through dashboards or monitoring systems. The final component of the system design is the database and reporting module, which stores detection results and generates maintenance reports. These reports help transportation authorities analyze road conditions, prioritize repairs, and implement proactive maintenance strategies.

V PROPOSED SYSTEM

The proposed system introduces an intelligent road defect detection framework that integrates advanced machine learning techniques with automated data collection and analysis mechanisms. The system aims to overcome the limitations of traditional road inspection methods by providing a scalable and efficient solution for monitoring road conditions. In the proposed framework, road surface data is collected continuously using cameras or sensors mounted on vehicles or mobile devices. This data acquisition process enables real-time monitoring of road conditions across large geographic areas. The collected images and video sequences are transmitted to a processing unit where they undergo preprocessing operations to enhance image quality and remove noise. The preprocessing stage includes filtering techniques, contrast enhancement, and normalization processes to ensure that important surface features are clearly visible. After preprocessing, the system extracts meaningful features from the road images using image-processing algorithms. These features capture the structural and textural characteristics of road surfaces that indicate potential defects. Feature extraction reduces computational complexity while preserving the most relevant information needed for classification. The extracted features are then used as inputs for the machine learning models implemented in the system.

The core component of the proposed system is the hybrid machine learning architecture that combines Long Short-Term Memory networks with Random Forest classifiers. The LSTM model analyzes sequential data obtained from video frames or sensor readings and captures temporal patterns in road surface conditions. By learning long-term dependencies in the data, the LSTM network can detect gradual changes in road surfaces that may indicate the early formation of cracks or potholes. This temporal analysis capability enhances the system’s ability to identify defects before they become severe. In parallel, the Random Forest classifier processes the extracted features to categorize road conditions into different classes such as normal surface, cracks, potholes, or other irregularities. Random Forest is chosen because of its robustness, ability to handle large feature sets, and high classification accuracy. The integration of LSTM and Random Forest creates a powerful hybrid system capable of analyzing both spatial and temporal patterns in road data. The final output of the system includes the detection and classification of road defects along with their locations in the captured images. These results are displayed through a monitoring interface that allows maintenance authorities to visualize road conditions and take appropriate actions. By providing accurate and timely information about road defects, the proposed system supports proactive maintenance strategies and contributes to safer and more efficient transportation infrastructure.

VI RESULTS & DISCUSSION

The experimental evaluation of the proposed road defect detection system demonstrates significant improvements in detection accuracy and reliability compared with traditional methods. The hybrid model combining LSTM and Random Forest successfully identifies various types of road defects, including cracks and potholes, under different environmental conditions. The LSTM component effectively captures temporal patterns in sequential road data, allowing the system to detect gradual changes in road surfaces over time. Meanwhile, the Random Forest classifier provides robust feature-based classification and reduces the impact of noise and data variability. Experimental results show that the hybrid approach achieves higher prediction accuracy and lower false detection rates compared with single-model approaches. The system also demonstrates strong generalization performance when tested on different road datasets. These results indicate that the integration of temporal learning and ensemble classification significantly enhances the performance of automated road defect detection systems and supports efficient road maintenance planning.

VII CONCLUSION

This study presented an intelligent road defect detection system that integrates Long Short-Term Memory networks and Random Forest classifiers to improve the accuracy and efficiency of automated road monitoring. Road defects such as cracks, potholes, and surface irregularities pose significant challenges to transportation safety and infrastructure management. Traditional inspection methods rely on manual surveys, which are time-consuming, expensive, and prone to human error. To address these limitations, the proposed system utilizes advanced machine learning techniques to analyze road surface images and sequential data collected from sensors or cameras. The LSTM network captures temporal patterns in road surface conditions and enables the detection of gradual changes that may indicate the early stages of defect formation. The Random Forest classifier performs accurate classification of road defects based on extracted features such as texture, edges, and surface irregularities. By combining these two models, the proposed hybrid framework leverages both temporal learning capabilities and robust ensemble classification techniques. Experimental results demonstrate that the system achieves improved detection accuracy and reduced false predictions compared with traditional image-processing approaches. The system is capable of identifying different types of road defects under varying environmental conditions, making it suitable for real-world road monitoring applications. In addition to improving detection performance, the proposed system supports proactive road maintenance by providing timely information about road surface conditions. This enables transportation authorities to prioritize repair activities and allocate resources more effectively. Overall, the proposed road defect detection framework contributes to the development of intelligent transportation systems and smart infrastructure management. Future research may focus on integrating deep learning models, real-time deployment using edge computing, and expanding datasets to further improve system performance and scalability.

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