

A Deep Learning framework for predictive maintenance of smart roads using IoT

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Abstract: This paper focuses on the utilisation of image data for classifying road conditions, particularly in scenarios containing loose gravel. The Internet of Things (IoT) enables efficient management and integration by connecting many application domains inside the city. Optimised traffic management, enhanced public transportation infrastructure, intelligent parking solutions, meticulous utility monitoring to promote conservation, improved waste management protocols, and increased public safety measures through advanced surveillance and expedited emergency response systems are tangible results of this Internet of Things-driven urban transformation. Government agencies, enterprises, and people must collaborate seamlessly to achieve success in this domain. This article presents an approach using deep learning and feature selection to predict when repairs will be necessary for the roadways of a smart transport system.

Keywords: Smart Transportation; smart roads; Internet of things; deep learning; maintenance prediction;

Introduction

The contemporary city landscape is swiftly evolving under the influence of the smart city paradigm. These contemporary urban environments can be characterized as intricate 'systems of systems, wherein the myriad subsystems are closely interwoven, exhibiting intricate dependencies. Such dependencies not only exist among the various systems but also between the diverse stakeholders representing different sectors. Navigating this complex terrain to achieve an effective design, engineering, and operation poses significant challenges. This complexity arises primarily due to the vast number of stakeholders involved, each bringing forward their requirements. Some of these requirements might be at odds with one another, and moreover, they tend to evolve over time [1].

IoT acts as a binding agent connecting various application areas within the city, facilitating efficient management and coordination. From a smart city perspective, IoT paves the way for collecting and analyzing voluminous data from diverse sensors and devices stationed across the urban landscape [4]. The derived insights are invaluable, promoting informed decision-making and ensuring optimal resource allocation.

A few tangible outcomes arising from this IoT-powered urban transformation encompass optimized traffic management, the enhancement of public transportation infrastructures, sophisticated parking solutions, vigilant monitoring of utilities to promote conservation, advanced waste management protocols, and the augmentation of public safety measures through upgraded surveillance and swift emergency response mechanisms [5-7]. Collaboration is fundamental in this domain, requiring synchronicity between governmental entities, private sector players, and the citizenry.

The advantages stemming from the integration of IoT in the urban matrix are manifold, ranging from enhanced resource management, an uplifted quality of life for inhabitants, and heightened sustainability, to streamlined city operations. Nevertheless, as we tread this path, it's crucial to be cognizant of the accompanying privacy and security concerns linked to the large-scale IoT deployments [8-9]. Ensuring the reliability and integrity of a smart city ecosystem hinges on effectively addressing these concerns.

The modern civilization is primarily characterized by pervasive connectivity and ubiquitous data exchanges among the devices connected over the Internet. Although the term IoT was coined towards the end of the past century [10], yet it has taken the next two decades to realize its true potential. In recent years IoT has lent its applications to a wide range of domains be it healthcare, utility services or transportation [11]. There has been a great range of complexities across IoT applications built over the past few years which makes it difficult to provide a universally acceptable definition. A generic definition to start with could be as simple as IoT being a technology for enabling interactions between cyber and physical realms by means of variegated sensors, actuators and communication protocols [12]. IoT applications involve seamless communication between the 'things' by means of machine-

to-machine (M2M) communication. Cloud computing also plays a major role in storing the massive data generated. Finally, the data collected by sensors and actuators are stored and processed to derive meaningful insight into it. But the entire ecosystem is depends on how these devices are communicating each other. Although different communication technologies can be used for accomplishing the same but the communication used mainly the wireless.

Predictive Maintenance allows you to get the most out of your equipment. The technique of Anomaly Detection or Fault Detection in the functioning of the equipment is the primary objective of any Predictive Maintenance strategy. AI mechanisms can help the machinery supervisor strategize maintenance tasks by detecting defects/anomalies early. A predictive maintenance process implemented using AI models typically consists of four steps data acquisition, raw data cleaning and preprocessing, data monitoring for anomaly detection and diagnosis using AI and finally anomaly prognosis using AI.

This paper presents a deep learning and feature selection based framework to predict road maintenance in a smart transportation system

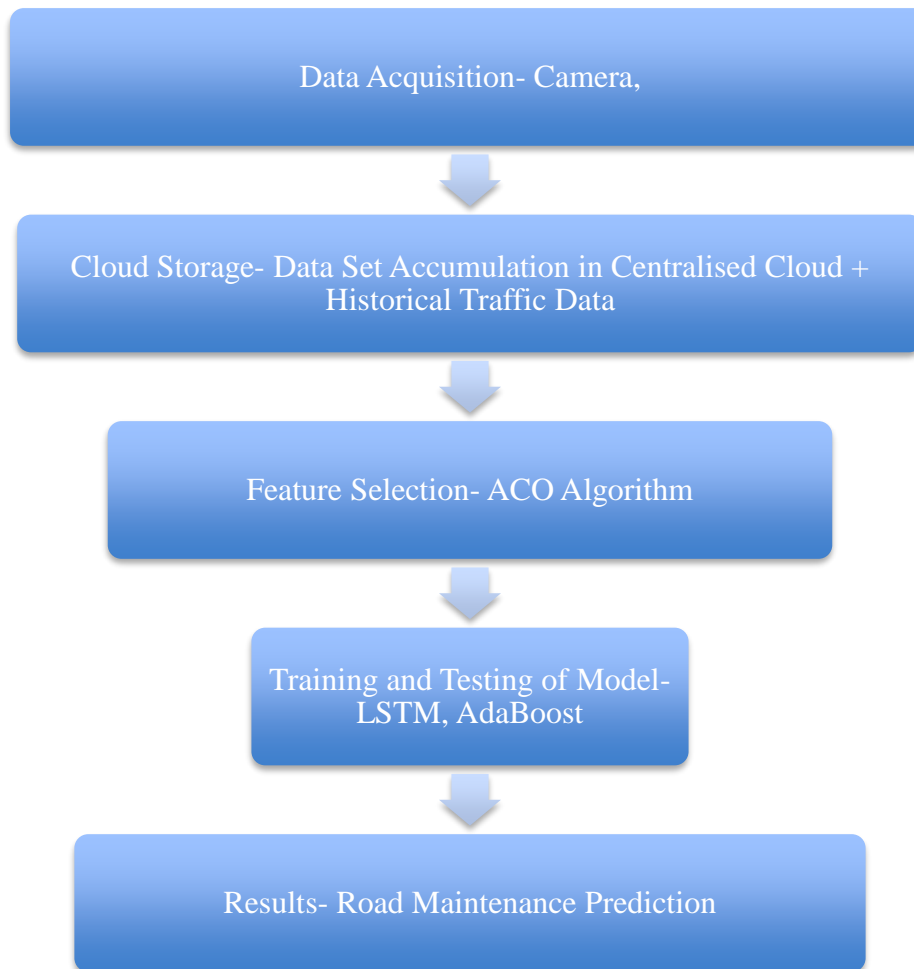


Figure 1: Internet of Vehicles and Deep Learning Enabled Intelligent Transportation System for Traffic Congestion Prediction

Integrations of the firefly technique and the ant colony optimization (ACO) algorithm [12] are prevalent in discussions on feature selection algorithms. The ACO algorithm is responsible for classification and feature continuity analysis, while the firefly method is tasked with picking data sub-bands pertinent to incursions. An apt example of this similarity is the relationship between optimizing ant colonies and the development of an algorithm.

Each dataset has a distinct base classification in the Adaboost Decision Tree, contingent upon the significance of each individual occurrence as decided by the outcomes of the base classifier applied to that instance. The instance's weight will increase in subsequent models if the classification is incorrect, but it will retain its original value if the categorization is accurate [13]. Forecasting has become more accessible with the use of Deep LSTM [14], a technique that employs memory cells. The memory cell functions as an accumulator, maintaining a record of preceding states. The deep learning classifier evaluates both the input value and the preceding states of adjacent nodes when predicting the state. This classifier use a convolutional operator and a transitional kernel to provide future predictions, built upon the encoding and prediction layers. Subsequently, the forecasting network is used, applied to both the initial state and the output of the encoding networks. The self-parameterized gate is used to get access to the sale. The memory cell processes state data by receiving input from the gate in this instance. The primary advantage of using gates and memory cells is their ability to maintain the continuity of information flow. It is shown in figure .

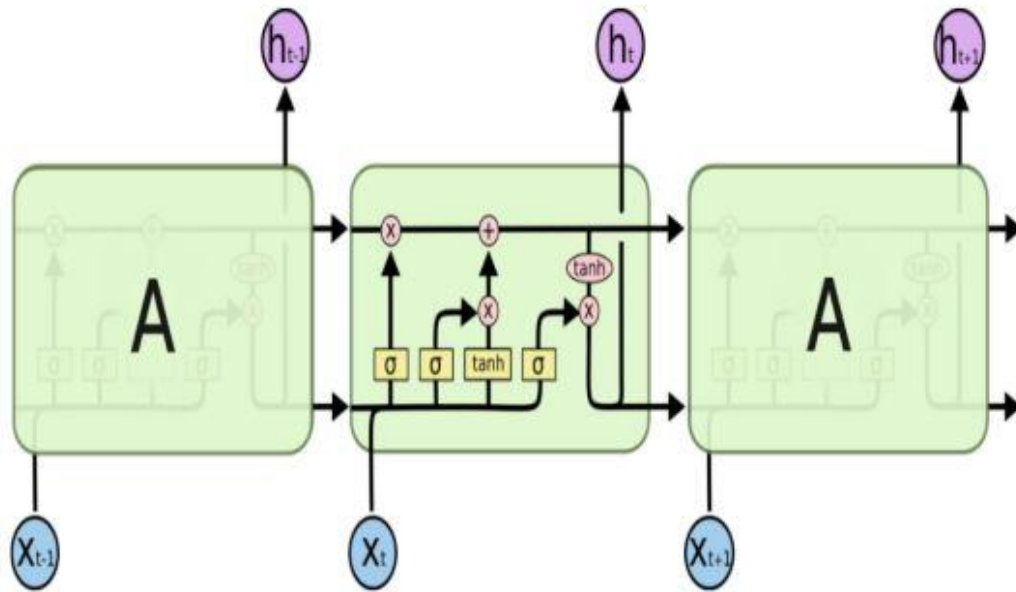


Figure 2: LSTM Model

Subsequently, the forecasting network is used, applied to both the initial state and the output of the encoding networks. The self-parameterized gate is used to access the sale. The memory cell processes state data as it gets input from the gate in this instance. The principal advantage of using gates with the memory cell is the preservation of a consistent data flow. The tensors used by this classifier are only three-dimensional, with spatially designated columns and rows. The tensors for input, hidden, and gates comprise this collection. Both the input cell and the cell states are represented by a vector, however.

Results and Discussion

In experimental set up, 200 images captured from camera are used. 150 CT scans are used to train classification model. 50 CT scan images are used to test the classification model. Results are presented in Figure 3.

$$\begin{aligned}
 accuracy &= (tp + tn)/N \\
 sensitivity &= tp_rate \\
 specificity &= tn_rate \\
 precision &= tp/(tp + fp)
 \end{aligned}$$

$$recall \frac{tp}{tp + fn} f_measure = 2 * ((precision * recall)/(precision + recall))$$

Where tp, tn, fp and fn represent the sum of a true positive, true negative, false positive and false negative, N labels the total number of elements. Results are shown in figure 5.

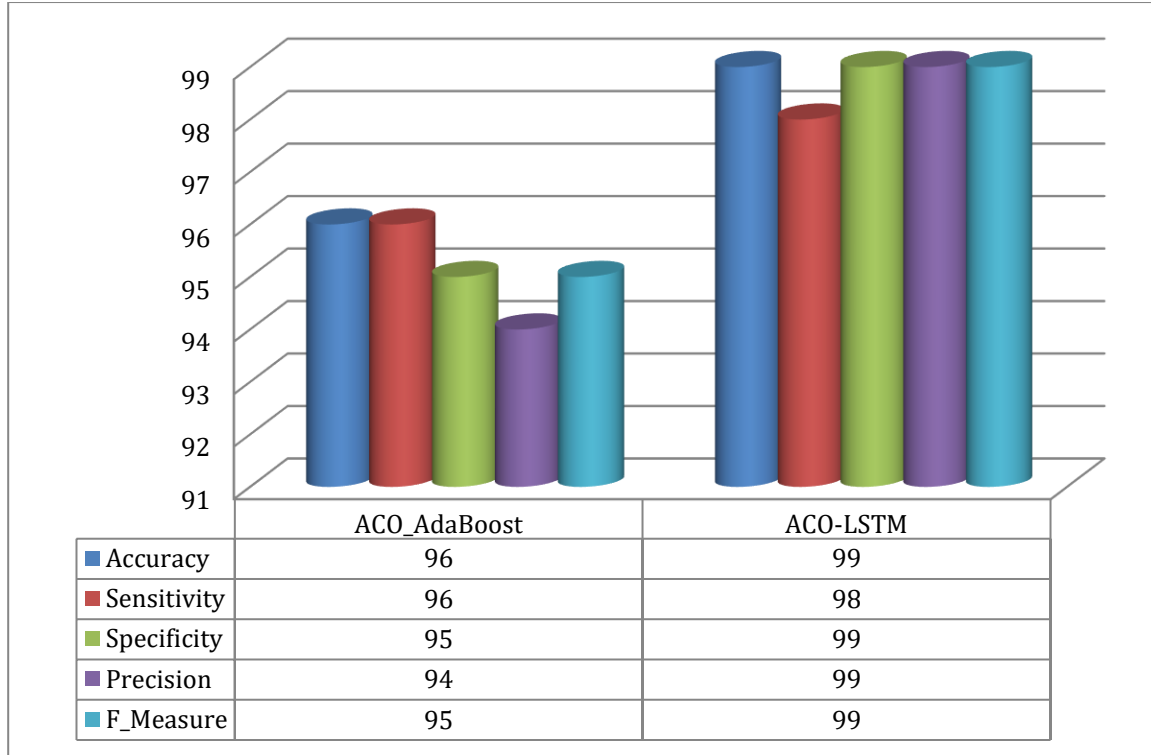


Figure 3: Result Comparison of AdaBoost and LSTM for road maintenance prediction

Conclusion

This research emphasises on the use of visual data to identify road conditions, specifically in settings with loose gravel. The Internet of Things (IoT) facilitates effective administration and integration by linking several application domains inside the city. This Internet of Things-driven urban transformation has yielded tangible results such as improved traffic management, enhanced public transportation infrastructure, intelligent parking solutions, meticulous utility monitoring to promote conservation, improved waste management protocols, and increased public safety measures via advanced surveillance and expedited emergency response systems. To be successful in this arena, government organisations, businesses, and individuals must work smoothly together. This article describes a method for utilising deep learning and feature selection to forecast when a smart transportation system's streets will need to be repaired.

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