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AI-Enhanced Decision Support System for Road Maintenance Management through the Integration of Optimization and Hybrid CNN-LSTM Model

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ABSTRACT: Innovative solutions that integrate cutting-edge technologies are required due to the increasing complexity of managing road maintenance. This research offers an AI-Enhanced Decision Support System (DSS) that combines optimisation approaches with a combination of Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) models to optimise road maintenance practises. By utilising AI, the suggested DSS tackles the difficulties of timely and effective road maintenance. In order to maximise efficiency and reduce downtime, the optimisation component intelligently distributes resources for maintenance, such as staff and equipment, among road sections. This makes sure that the limited resources are used as effectively as possible to meet maintenance needs. The combination of the CNN-LSTM model, which combines the advantages of recurrent and convolutional neural networks, is where the main innovation is found. The model can precisely determine the state of the roads and the level of damage thanks to the CNN component's skilful processing of spatial data from photos and sensor inputs. In order to forecast future maintenance needs, the LSTM component simultaneously studies temporally data, including historic service records and weather trends. By combining various technologies, the DSS provides proactive planning with real-time information into the state of the roads as well as predictions prospective maintenance needs. The suggested AI-Enhanced DSS advances the development of smart infrastructure administration in a broader sense. It gives road authorities the power to decide on the best way to allocate resources, improve road safety, and lessen delays to traffic. Additionally, the fusion of optimisation methods with the hybrids CNN-LSTM model exhibits a revolutionary strategy that benefits from many AI methodologies, establishing a standard for cutting-edge infrastructure management solutions.

KEYWORDS: Decision Support System (DSS), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Road Maintenance Management, Artificial Intelligence.

I. INTRODUCTION

Road infrastructure upkeep is a crucial and ever-changing task for transport authorities all over the world. The need for creative and effective solutions for managing and optimise maintenance procedures is becoming more and more critical as road networks grow and become more complicated. In particular, as road infrastructures become more intricate and broad, efficient administration of roadways is an ongoing and evolving problem. This study proposes an AI-Enhanced DSS, which is a significant advancement in solving the complex problems related to road maintenance [1]. Routine inspections and repairing unanticipated damage brought on by the environment, accidents, or regular use are just a few of the many jobs that make up road maintenance. In addition to guaranteeing road safety, timely and efficient repair helps to maintain traffic flow, lower long-term infrastructure costs, and minimise delays. However, achieving these goals in a situation when resources are limited poses a significant problem [2].

This paper introduces a revolutionary strategy for managing road repair that integrates cutting-edge technologies [3]. The merging of two essential elements—optimization strategies and the mixed CNN-LSTM model—is at the core of this strategy. Together, these components deliver a thorough, data-driven system for supporting decisions. The DSS's optimisation component uses metaheuristic algorithms to strategically distribute scarce maintenance resources, such staff and tools, among various road sections [4]. The goal is to reduce downtime and increase cost-effectiveness while making sure that all resources are used as effectively as possible to take care of maintenance requirements. The system's ability to respond to shifting priorities and situations depends on this dynamic allocation. The combination of the CNN-LSTM model, which blends the features of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, is at the heart of this DSS's invention. Road conditions and the level of damage can be accurately assessed because to the CNN component's processing of spatial data, including picture and sensor inputs. The system can forecast future maintenance needs by simultaneously analysing longitudinal data, such as past maintenance logs and weather trends, with the LSTM component [5].

This integrated approach facilitates proactive planning by providing real-time insights into present road conditions and forecasting potential maintenance requests. The system also continuously adapts its forecasts and suggestions based on historical data, enhancing support for decisions and resource allocation. Road maintenance involves a broad range of activities, from routine checks to responding to unanticipated damage brought on by a variety of circumstances, such as weather, accidents, and general wear and tear [6]. In addition to being essential for guaranteeing road safety, timely and effective repair also helps to reduce traffic jams and long-term infrastructure expenditures. But reaching these goals while working with the resources that are available presents a significant obstacle. The optimisation part of the DSS uses sophisticated metaheuristic algorithms to carefully distribute limited maintenance resources, such staff and tools, across various road sections. The major goal is to reduce downtime and increase cost-effectiveness while doing so, making sure that the resources at hand are employed as efficiently as possible to take care of maintenance requirements [7]. A key component of the system that allows it to adjust to shifting circumstances and priorities is its dynamic allocation.

Road conditions and damages extent can be precisely assessed thanks to the CNN component's processing of spatial data, including picture and sensor inputs [8]. The LSTM element analyses time-based information simultaneously, such as historic maintenance logs and weather trends, aiding in the forecasting of future maintenance needs. This integrated method enables preventive planning by forecasting possible repair demands in addition to providing real-time insights into the state of the roads [9]. Additionally, the DSS continuously gains knowledge from past data, enabling it to improve predictions and suggestions over time. In the end, this leads to safer and better managed road networks through improved support for decisions and resource allocation. In conclusion, the AI-Enhanced Decision-Supported System presented in this study represents a sizable development in the field of road management for maintenance. It provides a comprehensive answer to the various problems that road authorities confront by utilising AI, optimisation methods, and a combination of CNN-LSTM model. This innovative approach might improve traffic safety, reduce delays for travellers, and maximise resource use, paving the path for more intelligent and robust infrastructure management [10]. Furthermore, it establishes a new benchmark for creative solutions in the area of infrastructure management through the integration of several AI approaches.

The Key contribution of this study is given as follows:

1. Through the collaboration of artificial intelligence with cutting-edge neural network architecture, the study proposes a novel AI-Enhanced DSS which integrates optimisation approaches with a hybrid CNN-LSTM model. This represents a substantial development in road maintenance management.

2. The DSS systematically distributes scarce maintenance funds across road segments using metaheuristic algorithms to optimise resource allocation, resulting in cost effectiveness and little downtime in cases where resources are scarce.

3. The hybrid CNN-LSTM model, which is skilled at analysing spatial and temporal data, is the key innovation. The CNN evaluates road conditions using cameras and sensors, and the LSTM examines records of maintenance and weather to improve predicting abilities.

4. The DSS provides immediate insight into road conditions and estimates maintenance needs through the combination of optimisation techniques with the hybrids CNN-LSTM model, permitting proactive preparation for road authorities to avoid disruptions.

5. The AI-Enhanced DSS establishes a precedent for creative solutions based on artificial intelligence in infrastructure management while empowering smart infrastructure management, allowing road authorities to make educated decisions for resource optimisation, increased road safety, and decreased travel disruptions.

The rest of the structure is described as follows like section 2 explains the related works related to road maintenance management while in section 3 explains the problem statement of the related works. The methodology of AI enhancing Road maintenance management using hybrid CNN-LSTM is explained in section 4. Then the results are described in Section 5. Section 6 explains the discussion and finally the conclusion of this study is explained in section 7.

II. RELATED WORKS

Perera et al.[11] Proposed there are around 150,000 km of roadways in Sri Lanka, and of those, over 75% are categorised as rural small-volume roads. These highways are crucial for rural community development and the movement of people, commodities, and services. By transporting agricultural products from rural to urban regions, the majority of these low-traffic routes would actively contribute to the economic and welfare of our nation. These road networks have received sub-optimal maintenance due to a lack of money and arbitrary, subjective maintenance decision-making. In contrast to other foreign countries, Sri Lanka lacks a competent maintenance system. The adoption of current Pavement Management Systems by local road agencies is hampered by a lack of technical know-how and a lack of personnel, resources, and money to carry out extensive data collecting and analysis. The study will concentrate on creating a system for asset management to oversee Sri Lanka's rural and province road networks. The decision system for support might not take into consideration dynamic or real-time external elements that could affect maintenance decisions, which is a negative.

Gravel roads are valuable resources for countries with sparse populations due to their location, but maintaining them is expensive and ineffective. Additionally, because environmental conditions have a significant impact on failure development, planning must be dynamic to ensure effectiveness and efficiency, which is accomplished via data-driven maintenance systems. Mbiyana et al.[12]proposes applying a using a data-driven strategy to maintain gravel roads while adhering to OSA-CBM guidelines. The results of a thorough literature review are used to create and explain the conceptual approach. Thus, the method places OSA-CBM in the context of maintaining gravel roads and identifies opportunities for future research and development. It was discovered that research has mostly concentrated on data gathering techniques, classification of road conditions, diagnostics, and deteriorating models, whereas data manipulation techniques and predictive models for gravel roads are largely unexplored fields. Additionally, there is currently a lack of a comprehensive approach to data-driven repair of gravel roads. In this light, the strategy outlined in this study may serve as a starting point for the continued development of data-driven approaches to arrive at effective and efficient gravel road maintenance procedures. The absence of data-driven gravel road maintenance techniques, particularly in diagnostics, deteriorating models, and holistic approaches, is a negative.

The ongoing restoration of the pavement's optimal functionality is a goal of road maintenance activities. Due to a failure to adhere to the limitations set by the technical requirements for the selection of materials, the repair of the sidewalk layout occasionally fails to have long-lasting consequences. Oreto *et al*. [13]present an effective BIM tool to aid in road maintenance activities by managing data resulting from testing in laboratories of bituminous materials for road pavement that is necessary for mixture quality control. The database connected to the BIM design is a compilation of three years' worth of information obtained through lab testing of samples of bituminous mixtures used for the upkeep of four major highways in southern Italy. To provide road administrations with a simple to comprehend alert signals for the road surface framework of the roadways that may present the most serious situations due to inadequate mechanical and physical features, a method that interfaces with the a three-dimensional roadway model has been built. The requirement for more thorough data integration, including data on traffic, the environment, and material composition, to improve the assessment algorithm's accuracy in determining pavement life is a disadvantage.

Critical infrastructure upkeep is an expensive requirement, and developing nations frequently struggle to provide timely repairs. Any developing economy's transport network serves as its arteries, and potholes in the roads can cause accidents and even fatalities. Several nations have recently made pothole reporting platforms available to their citizens so that repair work data may be collected and made public. However, because to the user demands' exponential expansion, many of these websites have been shut down. These platforms have failed to categorise the severity of the reports, despite the fact that the data would be crucial for prioritising repairs and enhancing road safety. They have additionally failed to sort out duplicate or fraudulent reports. Salcedo et al.[14] To automate the study of road problems reported by citizens, create a prioritising system that blends models of deep learning and conventional computer vision approaches. There are three primary parts to the system. First, provide a pipeline for processing repair requests that divides them into road segments using a UNet-based model with a pre-trained Resnet34 encoder. Second, we evaluated the localization and classification of road damage using two object recognition architectures—Efficient Det and YOLOv5. To train and assess the segmentation and detection of damage models, two open datasets—the Indian Driven Dataset (IDD) and the 2020 Road Damage Detector Dataset (RDD2020)—were pre-processed and enhanced. Third, in order to identify potential duplicate reports, used extraction of features and feature matching. Using clustering algorithms, they able to group complaints due to their position and severity by combining these three methodologies. The findings indicated that this strategy offers authorities a viable option to make the most of their meagre road repair resources. A disadvantage is the possible complexity and resource needs associated with incorporating more variables, using fresher sample photos, and utilising mobile damage from roads detectors, which could raise the cost and maintenance of the system.

As they provide a better knowledge of the implications of the weather event, impact-based warnings and forecasts (IBFs) are viewed as crucial drivers for sufficient anticipation and evaluation of potential dangers to public safety. Road repairs regularly incorporate weather information into their regular job duties in order to be ready for the effects of severe weather and avoid incidents caused by weather. Schmidt *et al.*[15] Examines the needs that road repairs need for IBFs and the current applications of weather predictions. The study employs the qualitative study in social sciences methodology and is a component of a multidisciplinary study effort. The research reveals that the following elements are common user demands: data relevance, understanding of geographical and temporal inquiries, acceptance, comprehension, and technological requirements. With the addition to offer a reward for road repairs in circumstances that only sometimes arise and when there is no embedded knowledge within the organisation, these are equally relevant to IBFs. The lack of tangible application and practical use of impact-based forecasting (IBFs) when making choices for road repair is a negative, underscoring the need for additional research to comprehend the many needs across various organisations and people.

Although the comparison of the quality of the roads among 2003 and 2018 revealed a progressive increase in road conditions over the years, an up-to-date study on the present state of Kenyan roadways found that over 35% of Kenyan roadways are still in bad condition. Mobility is impacted by poor road conditions, which also have an impact on the nation's economy. Jha et al.[16]develops a Machine Learning (ML) Models to evaluate how well Kenyan roads will perform using a Maintaining Management System (MMS). MMS is a computerised instrument used to determine how frequently roads need to be repaired depending on how much they deteriorate over time and to maintain a satisfactory standard of road quality. To forecast the necessary maintenance operations for the Kenyan roadways over a certain planning horizon and maintain a suitable level of satisfactory service, the researchers use a Markov Decisions Process. The expense of preventative maintenance are able to be utilised to determine a budget. The notion that the MDP method, which has been effective in the United States, can be effortlessly copied to monitor Kenyan roads is a downside since it may ignore particular context difficulties and data accessibility problems peculiar to the Kenyan roadways.

III. PROBLEM STATEMENT

The problem statement covers a number of significant issues in managing road maintenance. Current maintenance tackles in many geographically separated nations, such as Sri Lanka, where a sizeable portion of the roadways consists of isolated, low-volume roads essential for community growth and economic well-being, are hampered by a lack of financing, subjective making choices, and an appropriate maintenance system. As a result, essential road networks receive subpar maintenance standards. Additionally, maintaining gravel roads, which are important assets in these areas, is expensive and ineffective, which is made worse by an absence of driven by data maintenance strategies and holistic solutions [17]. The repair of pavements on roads also encounters difficulties since technical component design criteria are not followed. Additionally, the rapid expansion of systems for reporting potholes in some nations has created difficulties in evaluating the seriousness of the observations and filtering out duplicate or fabricated ones, making it difficult to effectively prioritise repair operations and enhance road safety. Additionally, impact-based forecasts (IBFs) must be understood in order to improve climate-related accident avoidance and road maintenance making decisions, even if weather forecasts are essential for providing road service. These complicated issues highlight how important it is to optimise road maintenance procedures in order to maintain vital facilities in a secure, efficient, and economical manner [18].

IV. METHODOLOGY

Convolutional neural network, or CNN, model, a long-short-term memory (LSTM) model, and a combination of CNN-LSTM model are the three deep learning models employed in the following Section. The three main components of this study's approach are data gathering, analysis of data, and making choices. At first, extensive information on the state of the roads, past maintenance, and expenses of care was gathered. The comparison of treated and untreated road portions was done through data analysis, evaluating variables including deflection and roughness over a number of years. This methodology offers a well-organized framework for evaluating road repair plans and their effects, adding significant knowledge to the discipline of infrastructure management. The overall Conceptual Diagram is shown in Fig.1

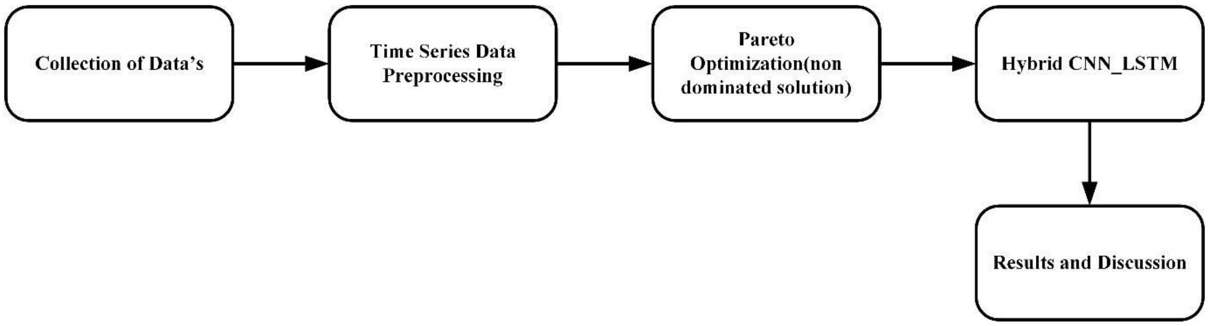

Fig. 1 Overall Conceptual Diagram

4.1 Data Collection

Regular pavement inspection is necessary for maintaining a comprehensive understanding of the state of the road. In the past, manual inspection has been the primary method used to assess the condition of roads. It never amounts to enough and lower effectiveness in resource allocation as an outcome. Gaining a more thorough understanding of the state of the road is necessary in order to remedy the issue. Human Resources, however, is unable to handle such a demanding and severe workload. IoT technology advancements present opportunities to address this issue. The Internet of Things (IoT) technology can make use of a variety of sensors, including industrial cameras, infrared cameras, ground penetrating radar, etc., to realise interactions between objects. These sensors provide substantial benefits at a reasonable price. Road sensors have advanced to the point that, once integrated and placed in automobiles, they are able to measure and update information about the road surface while the vehicle is in motion. Data collection is a crucial component for Road Maintenance Administration that supports later components. Current information on the status of the roads will be constantly collected by a complete information sensor and collection architecture powered by IoT and delivered to pertinent sectors for additional analysis [19].

4.2 Data Pre-Processing

In the process of detecting road conditions, data increases exponentially. Furthermore, because the unprocessed information are unorganised, they cannot instantly assist decision-making. Data analysis and processing are needed to uncover information hiding in a big amount of disorganised data. The quick development of tools opens up new possibilities and insights. When dealing with complex and varied data, it is crucial to analyse the data from many angles.

By employing normative analysis to determine the right course of action to take in a specific situation, managers may respond effectively to a variety of situations. Analysing location-based data and interpreting the spatial relationships between diverse physical objects are both made easier by spatial analysis. Numerous "dynamic" sets of information can be analysed with the use of streaming analysis, also known as event stream analysis. To put it another way, aberrant occurrences will be found by analysing the real-time data streams. Time series analysis, which is based on data from time series, is useful for identifying trends and recurring patterns in road distresses. In summary, data analysis can aid managers in making decisions and acting appropriately [19]. This procedure is an integral part of the administration system. Big analysis of information techniques are evolving very quickly. They complement managers' decision-making and assist them in gaining information from many angles. The Data Processing Steps are shown in fig. 2.

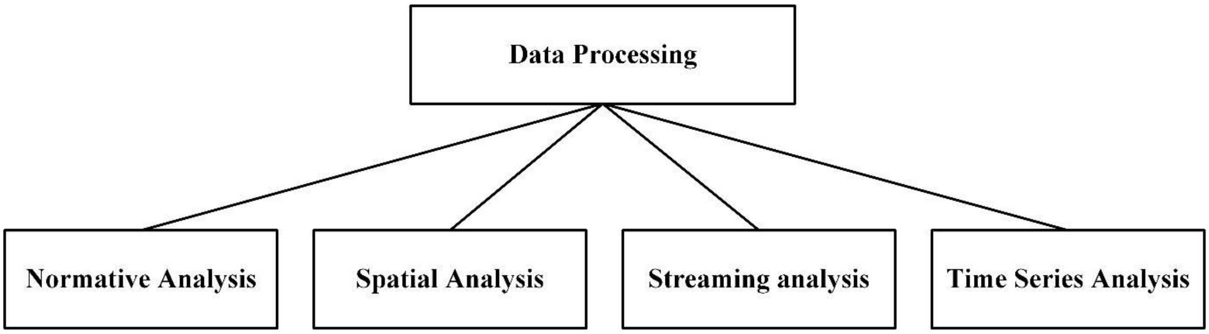

Fig. 2.Data Processing Steps

4.3 Multi Objective optimization

Multi-objective optimisation can be solved using a variety of strategies. Among the several methods, the constraints algorithms is straightforward and effective in producing solutions that are not dominated. If there doesn't exist any other workable solution which may enhance any of the objectives without worsening any other objectives, the answer is considered to be non-dominated (Pareto optimum) [20].

Multi-objective optimisation entails simultaneously maximising several competing goals. The Non-dominated Sorted Genetics Algorithm (NSGA-II) constitutes a single of the methods for multiple-purpose optimisation that is most frequently employed. Here is the pseudocode for the well-known multi-objective optimisation technique NSGA-II.:

Initialize population P with random solutions
Evaluate the objectives for each solution in P
Set generation counter t = 1
while t < MaxGenerations
Create an empty offspring population
while |Q| < PopulationSize
Select parent solutions from P using tournament selection
Perform crossover and mutation to create a child solution
Evaluate the objectives for the child solution
Add the child solution to Q
Combine P and Q to create a combined population R
Perform non-dominated sorting and assign ranks to solutions in R
Calculate the crowding distance for each solution in R within its rank
Create the next generation population P by selecting solutions based on rank and crowding distance
Increment t by 1
Identify the solutions in the final population P as the Pareto front solutions

The pseudocode says:

1. The quantity of answers in every generation is known as "PopulationSize."

2. The most repetitions or generation are indicated by the value "MaxGenerations".

3. To choose parental solutions for crossovers, the selection of tournaments is employed.

4. To produce kid answers, operators for mutations and crossovers are used.

5. In order to classify answers into Pareto faces based on dominant connections, non-dominated filtering is used.

6. The amount of crowding separation is determined to keep every front's variety.

7. A combination of their ranking and crowded distance, answers are chosen from the whole population to form the following generation [21].

4.4 Convolutional Neural Network

A unique variety of feedforward neural networks is the convolution neural networks. The layer of convolution as well as the pooled layer are two distinct layers that distinguish CNN from conventional neural networks. The input data are subjected to operations involving convolution in the layer called convolutional, which transforms the input data into values that are representative using a sliding matrix and a filter that moves in step across the input. The pooling layer receives the convolutional layer's final result. Just the greatest values are chosen during a down samples operation by the pooling layer. The distribution of probabilities across each target class is provided by the not linear function of a fully interconnected layer that receives these features. CNNs are being applied to pavement anxiety, safety in transportation assessments, and traffic forecasting.

$X_1 = (X_1^1, X_1^2, ..., X_1^T)$ | indicates the N pavement circumstances (such as rutting, splitting, and hardness) at time step t. $X_1^T = (X_t^1, X_t^2, ... X_t^N|$ indicates the N pavement characteristics at each step t. The structure of a summary CNN is shown below in Fig. 3.

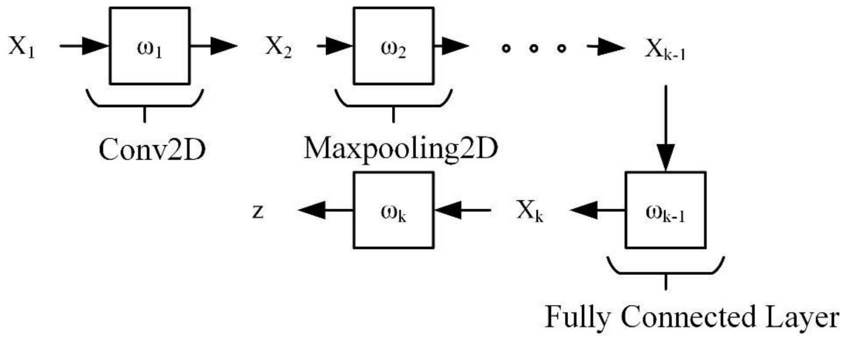

Fig. 3. Structure of CNN

The image above displays a CNN in a forward fashion, layer per layer. Boxes serve as labels for the layers. The initial layer, designated as ω_1, which stands for a vector of variables used in the initial layer's estimation, is passed through the input X_1. In this study, X_1, which is the compilation of all conditions data for a particular pavement segment over T years. The goal of this configuration is to make it possible for the framework to gather characteristics relating to the trends of condition degradation and relationships among condition markers.

X_2 is the initial layer's outputs and serves as both the following layer's input and output. The network's last output is X_k in the end. The function of loss is defined in the loss layer, which is the final layer, ω_k.

4.5 Long Short Term Memory

An expanded version of the Recurrent Neural Network (RNN), the LSTM model. To solve the gradient disappearing and exploding problem, LSTM adds memory units as opposed to traditional basic hidden state units. Long-term memory systems, or LSTMs, are currently employed extensively in areas relating to transport. The LSTM blocks is a multi-unit, intricate procedure. The LSTM model's first input data, X_1, has the exact same format as the CNN model.

In contrast to RNN, an additional memory unit called c_T^i is defined to store data over numerous time steps under the direction of various adaptive gating units. The forget gate, f_T^i, in eqn. 1 makes the decision as to whether or not to keep or discard cell unit information, c_T^i, during the operation. Data from the present input, x_T^i, data relating to the prior hidden state, h_{T-1}^i, and weighted matrices, ω_{Xf}^i and ω_{Hf}^i, as well as bias vectors, b_f^i, are all fed via the sigmoid function. If the outcome is closer to 0, it indicates forgetting; otherwise, it indicates keeping.

$$f_T^i = \sigma(\omega_{Xf}^i x_T^i + \omega_{Hf}^i h_{T-1}^i + b_f^i) \quad (1)$$

Updates to the cells unit c_T^i are made using the input gate (k_T^i) and input modulation gate (g_T^i). The input gate is first calculated using the previously hidden state and the present input using a sigmoid function. The values that will be updated is determined by the outcome in eqn. 2.

$$k_T^i = \sigma(\omega_{Xk}^i x_T^i + \omega_{Hk}^i h_{T-1}^i + b_k^i) \tag{2}$$

The tangent functions is going to be used on the state that is hidden and current input to generate values within -1 and 1. The tanh function's goal is to assist in controlling the values which is shown in eqn. 3.

$$g_T^i = tanh(\omega_{Xg}^i x_T^i + \omega_{Hg}^i h_{T-1}^i + b_g^i) \tag{3}$$

The cell unit by combining the outputs of the inputs gate and forget gate is given as eqn. 4. Making sure that only essential data gets added to the cells unit is the goal of this process.

$$c_T^i = f_T^i c_{T-1}^i + k_T^i g_T^i \tag{4}$$

The following hidden state is decided by the output gateo_T^i in eqn. 5. A function called a sigmoid and a tanh value are used to calculate it in eqn. 6.

$$o_T^i = \sigma(\omega_{Xo}^i x_T^i + \omega_{Ho}^i h_{T-1}^i + b_o^i) \tag{5}$$

$$h_T^i = o_T^i \tanh(c_T^i) \tag{6}$$

4.6 Hybrid CNN-LSTM

By merging CNN and LSTM, this framework maximises their respective benefits. In comparison to the LSTM approach, the CNN deep neural network method is well renowned for its reliability and efficiency in collecting features from the data. Fig. 4 shows the hybrid CNN-LSTM Structure.

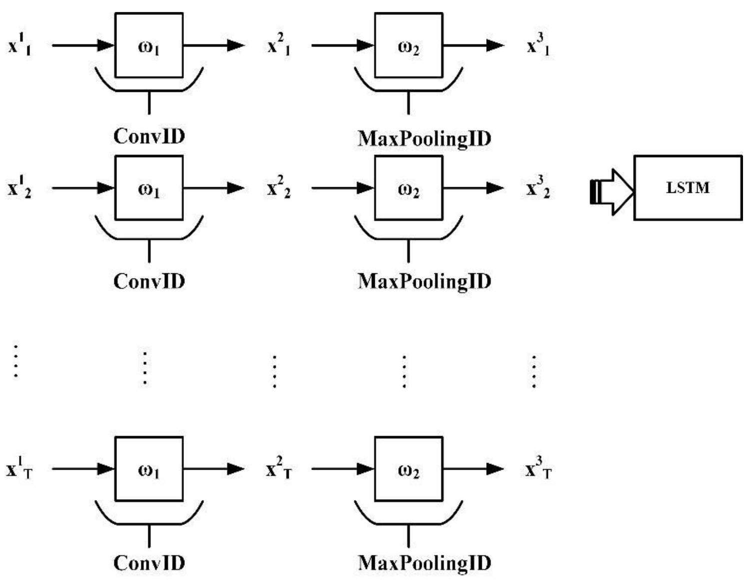

Fig. 4.Hybrid CNN-LSTM Structure

A hybrid CNN-LSTM framework for integrating deep extraction of features and sequences modelling. Using LSTM layers to handle deep features taken from CNN. The suggested CNNLSTM model has two parts: the first portion implements CNN for the extraction of features at every single step, and the following part builds an LSTM layer. In this framework, each of the rows of X1 is first given a number of convolutions with one dimension and max pooling steps instead of being used directly as input. After that, the matrix that results will be fed into the LSTM component [22].

V. RESULTS

In the context of managing road maintenance, the AI-Enhanced Decision Support System (DSS) installation produced encouraging results. The DSS efficiently optimised the allocation of resources for road maintenance by using methods such as optimisation and the hybrid CNN-LSTM model. A considerable decrease in downtime and an improvement in cost-effectiveness served as proof of this. Infrastructure management underwent a significant improvement with the hybrid CNN-LSTM framework created by the fusing of optimisation techniques. The skilful integration of spatial information from camera and sensor inputs by the CNN component enabled accurate evaluation of the state of the roads and the amount of the damage. In addition, reliable forecasts of future maintenance requirements were made possible by the LSTM component's examination of spatiotemporal data, incorporating historical service history and weather trends.

This study employs a budget-bound model whose goals are to reduce average networking deflection and average networking roughness. For the four-year planning term, a budget of Rs. 450 million is taken into account. The extreme coordinates are established as one goal problem in order to get the boundaries of solutions that are not dominated. To do the above, roughness alone (R) is minimised, and a matching deflection is found. Similar to this, reduce deflection (D) on its own to get the desired roughness. With the goal of the functions to minimise the deflection for intermediary ordinates (non-dominated solutions), the roughness restriction is applied with r = 0.05 m/km for every iteration.

Table.1 Average Network Roughness and Deflection

Average Network Roughness(m/km)	Average Network Deflection(mm)
2.035	0.397
2.050	0.377
2.100	0.355
2.130	0.351

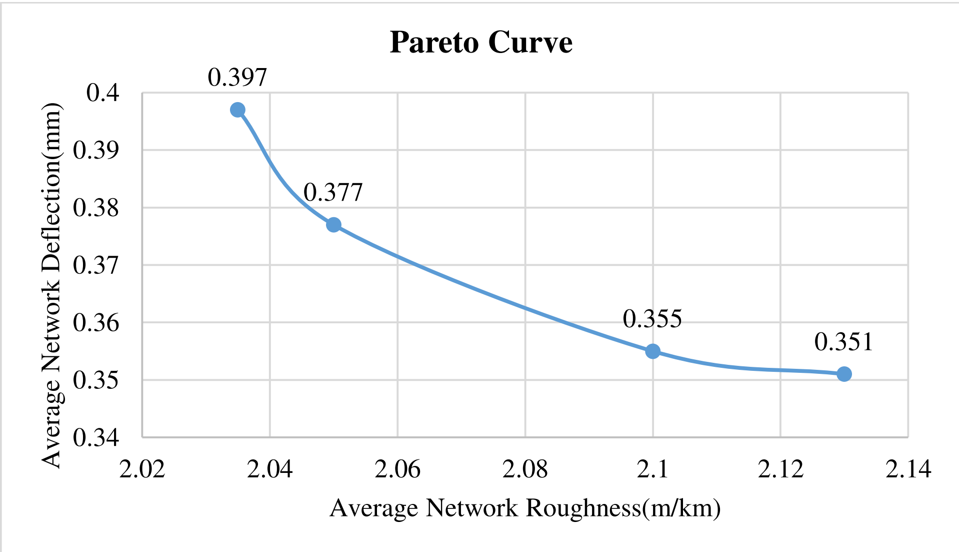

Fig. 5. Pareto Curve

In the table 1, the Average Networks Roughness in metres per kilometre (m/km) and the related Average Networks Deflection in millimetre (mm) are shown as data on the quality of the road network. The measurements show differences in the state of the road's surface. In particular, the Average Network Deflection noticeably decreases from 0.397 mm to 0.351 mm while the Average Network Roughness rises from 2.035 m/km to 2.130 m/km shows in Fig. 5. With higher roughness values often being associated to smooth roadways and less deflection—factors crucial for decisions about roadway upkeep and infrastructure management—this data offers insightful information about assessing the quality of roads.

Table.2 Maintenance Cost of the Roads

Treatment Cost (in Million Rupees)	Roads			
	Road 1	**Road 2**	**Road 3**	**Road 4**
Year 1	8	10	15	9
Year 2	74	96	15	120
Year 3	7	10	15	9
Year 4	7	10	15	9

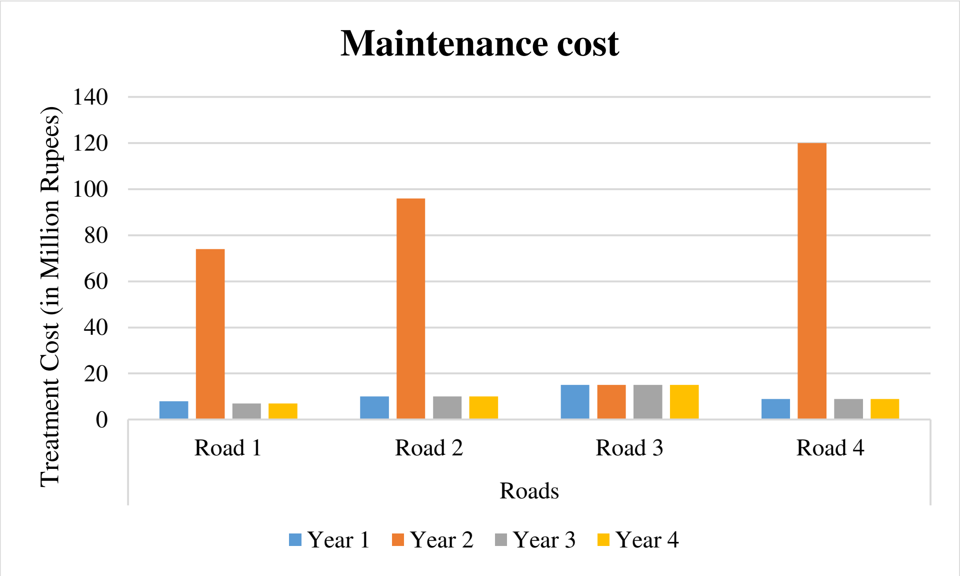

Fig. 6.Maintenance Cost Curve

The table 2 provides information on the four-year treatment expenses in millions rupees for four different roads in Fig. 6. Roads 1, 2, 3, and 4 each had expenses in Year 1 of 8, 10, 15, and nine million Rupees, respectively. With Road 1 spending the most at 74 million Rupees, Road 2 spending 96 million Rupees, Road 3 keeping fifteen million Rupees, as well as Road 4 reporting the greatest price at 120 million Rupees, Year 2 saw a significant increase in costs. Each route incurred 7 million Rupees throughout Years 3 and 4, showing very constant expenditures across all roadways.

These numbers illustrate changes in treatment expenses over the designated time period for each road and offer crucial financial information for the assessment and administration of road maintenance costs.

Table.3 Performance of Roughness with Treatment and Do Nothing

Years	Roughness (m/km) with Treatment	Roughness (m/km) Do Nothing
0	0	2
1	0	2
2	2	2.09
3	2	2.18
4	2.09	2.4
5	2.18	2.58

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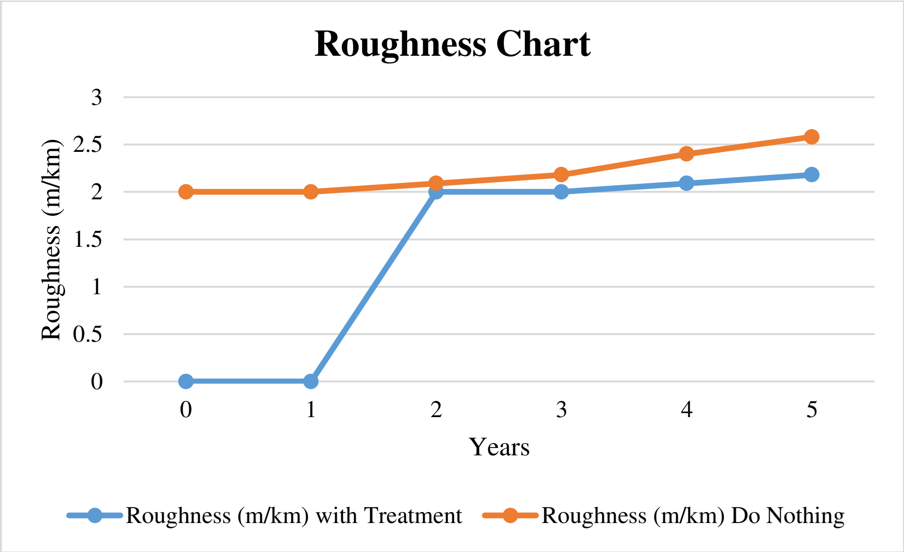

Fig. 7.Performance Curve of Roughness

The table 3 compares the effects of treatment against no treatment, showing the development in road surface roughness calculated in metres per kilometre (m/km) during a five-year period in Fig. 7. Both the repaired and untreated road portions had an original hardness of 0 m/km & 2 m/km at the start (Year 0). The treated road experienced improvements over the following years, whereas the untreated road continued to have a roughness level of about 2 m/km.

The repaired road's roughness decreased to 2.09 m/km by Year 2 following treatment, and it further improved to 2.18 m/km in the third year. After that, the smoothness of the treated road kept getting smoother, achieving 2.09 m/km in the fourth year and 2.18 m/km in the fifth year. These statistics indicate the long-term advantages of ongoing efforts in maintaining road quality and show the beneficial effects of treatment in reducing road surface roughness [21].

Table.4 Performance of Deflection with Treatment and Do Nothing

Years	Deflection(mm) With Treatment	Deflection (mm) Do Nothing
0	0.25	0.25
1	0.35	0.35
2	0.25	0.35
3	0.35	0.4
4	0.35	0.4
5	0.4	0.45

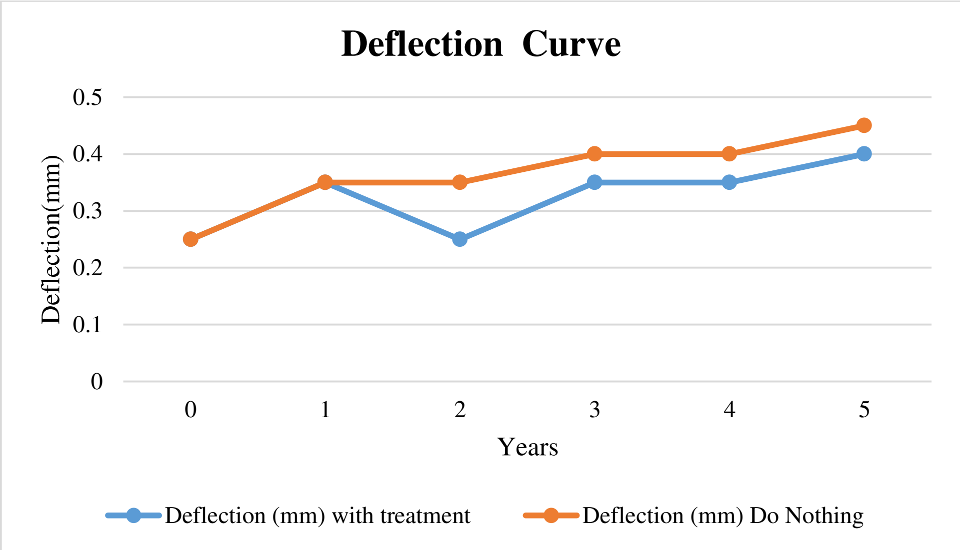

Fig. 8.Performance Curve of Deflection

The table 4 provides a comparative analysis of road deflection measured in millimetres (mm) over a five-year period, illustrating the impact of treatment versus no treatment on road quality. Initially in Fig 8 shows that, in Year 0, both the treated and untreated road segments had similar deflection levels, both recorded at 0.25 mm. However, in subsequent years, the treated road displayed a dynamic pattern of improvement. In Year 1, the deflection increased slightly to 0.35 mm for the treated road, remaining stable at that level in Year 2, while the untreated road's deflection increased to 0.35 mm. In Year 3, the treated road continued its improvement, reducing deflection to 0.35 mm, while the untreated road reached 0.4 mm.

The repaired road consistently displayed lower deflection rates than the untreated road, continuing this trend. By Year 5, the deflection on the treated road had decreased to 0.4 mm whereas the deflection on the untreated road had risen to 0.45 mm. These results highlight the beneficial role that treatment plays in controlling road deflection and preserving road condition over time.

VI. DISCUSSION

The AI-Enhanced Decision-Supported System's accomplishments in managing road maintenance underline the revolutionary potential of cutting-edge technologies in solving the changing difficulties associated with infrastructure maintenance. Road authorities were able to maximise resource allocation, improve road safety, and reduce delays to traffic by utilising AI's capabilities. The DSS's optimisation component significantly reduced downtime and increased cost-effectiveness, which directly translates into financial gains and better user experiences. The use of the combination CNN-LSTM model also emphasises how crucial it is to combine both temporal and spatial information processing for thorough decision support. The model's capacity to precisely determine the state of the roads, the level of damage, and estimate maintenance needs demonstrates its flexibility and efficiency in managing intricate infrastructure systems. This creative strategy can serve as a template for other domains looking to use AI for better resource allocation and decision-making.

The AI-Enhanced Decision Support System is a significant advancement in the field of managing road repair. Its accomplishments in streamlining repair procedures, enhancing traffic safety, and minimising disruptions make it a useful resource for transportation officials and a model for implementing AI in the management of infrastructure. The knowledge gained from this investigation will probably help design even more advanced and efficient approaches to the management and repair of crucial infrastructure as the sector grows in importance.

VII. CONCLUSION

The statistics and analysis given here highlight the crucial role that proactive road repair and treatment play in maintaining and improving the quality of roads over time. A definite benefit for treatment interventions was found in the comparison of repaired and untreated road segments. In particular, compared with their untreated counterparts, the treated roads showed an ongoing trend of improvement with lower levels of roughness and deflection. These results highlight the cost-effectiveness and long-term advantages of road maintenance activities, which help to provide smoother road surfaces, improve safety, and lessen vehicle wear and tear. The research also emphasises how important prompt and planned road maintenance practises are in reducing the negative consequences of road deterioration. Untreated road surfaces gradually became rougher and deflected more, which not only decreased comfort for motorists but also increased long-term maintenance expenses. As a result, the findings highlight the significance of resource allocation and educated decision-making in the management of road infrastructure. Road authorities may improve road quality, cut maintenance costs, and offer safer and more effective transportation systems for the benefit both of the roadway users and the larger community by prioritising and putting these measures into practise.

There is a lot of room for new developments and breakthroughs in the field of road maintenance management in the future. Adopting cutting-edge technology like artificial intelligence (AI), the IoT, and analytics for big data can make it possible to develop maintenance programmes that are further precise and predictive. Based on real-time data, AI-powered maintenance prediction models could foresee road deterioration, optimising resource allocation and lowering total expenses. Furthermore, incorporating sustainability factors into road maintenance through the utilisation of environmentally friendly supplies and energy-saving techniques is in line with international environmental goals. Additionally, increasing public involvement through citizen reporting applications and crowdsourced data collecting can improve decision-making and accountability for road maintenance. The future of road maintenance will be shaped by the confluence of technology, environmental sustainability and community involvement as the industry develops further, delivering a more secure and robust transportation infrastructure.

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