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ORIGINAL RESEARCH ARTICLE

Transportation logistics monitoring for transportation systems using the machine learning

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ABSTRACT

To decrease the number of accidents, Transportation Systems (TS) work to increase traffic efficiency and vehicular flow in urban areas. The production of datasets to carry out an in-depth analysis of the data using machine learning techniques is made possible by the generation of huge volumes of data generated by all the digital devices connected to the transportation network. This paper proposed a machine learning technique called Gradient Descent K-Nearest Neighbors (GD-KNN) for transportation logistics monitoring to improve route optimization, demand forecasting, vehicle maintenance, real-time monitoring, freight optimization, risk assessment, and continuous improvement. By harnessing data from various sources such as GPS devices, sensors, telemetric, and historical transportation data, machine learning algorithms can analyze and process this data to make accurate predictions and recommendations. The collected dataset was pre-processed using z-score normalization, and then Independent Component Analysis (ICA) was applied for the feature extraction process. Real-time monitoring enables the detection of anomalies and delays, providing alerts for timely actions. Freight optimization is achieved by analyzing parameters like weight, size, and delivery locations, resulting in cost reduction and improved load balancing. GD-KNN assesses risks and security threats using data from security systems, ensuring the safety of goods and personnel. Continuous learning allows the system to adapt to changing conditions and improve predictions over time. Overall, GD-KNN empowers transportation logistics monitoring to optimize operations, enhance customer service, and reduce costs in transportation systems.

Keywords: transportation systems (TS); z-score normalization; independent component analysis (ICA); gradient descent k-nearest neighbors (GD-KNN); machine learning

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1. Introduction

People's living standards have increased as a result of the social industrialization process acceleration, which has also led to significant advancements in clothes, food, housing, and transportation. When traveling, individuals need to think about vehicles. The financial burdens brought on by traffic congestion in the present economic climate of urban congestion cannot be calculated. A reduction in people's quality of life will result from pollution in the environment brought on by automobile exhaust emissions, which will also bring personal annoyance as a result of traffic congestion. Therefore, academics' attention has shifted to the development and implementation of intelligent transportation systems for the purpose of monitoring traffic conditions[1]. There are many variables that contribute to the global phenomena of traffic congestion, including high population density, the growth of motor automobiles and related infrastructures, and the emergence of ridesharing and delivery services. Investigators have described congestion in a number of ways. In the context of traffic flow, the word "congestion" is most often used when travel demand exceeds road capacity. From the standpoint of delays and travel times, congestion occurs when a large number of cars impede the regular flow of traffic, adding extra travel time[2].

The transportation industry is vital to the development process. Numerous factors, including the availability of commodities, passenger mobility, logistics, etc., influence the need for transportation. As a result, logistics-based supply chain connections between customers and the supply chain group include transportation as a crucial and important component. Providing the correct goods, in the right situations, in the right volumes, at the right location, at the right moment, with the right price, and for the right client is the broad definition of logistics[3]. The use of logistics links several operations or activities that might combine to produce an excellent outcome or helpful item. As a consequence, effective logistic management is necessary to complete the jobs quickly and effectively. This can only be achieved with proper planning and effective utilization of transport services. This is beneficial for company growth and building a solid network of contacts between the readily available raw material providers everywhere and the final consumers[4]. A type of artificial intelligence called machine learning enables computers to continuously learn from data and improve their performance without explicit programming. Monitoring systems for transportation logistics may glean useful information from massive volumes of data produced by a variety of sources, including sensors, GPS devices, telematics systems, and even social media, by using the power of machine learning algorithms[5]. Monitoring for transportation logistics is the procedure of gathering, examining, and managing data on the flow of commodities, vehicles, and resources within a transportation system.

Guarantee an efficient and successful transfer of products and resources from one point to another one; it entails tracking and monitoring a variety of transportation activities involving vehicle location, condition, performance, and environmental conditions[6]. Logistics and supply chain management are strongly related to the transportation system. It entails the organization, coordination, and performance of tasks linked to the transportation, storage, and utilization of products. To guarantee prompt and affordable delivery, this scope comprises inventory management, warehousing, order fulfilment, and transportation planning[7]. Managing traffic effectively is a crucial component of the transportation system. Increasing general mobility and shortened travel times, entails monitoring and regulating traffic flow, enhancing signal timings, managing congestion, and integrating intelligent transportation systems (ITS)[8]. The growth of regions and nations' economies depends heavily on the transportation infrastructure. By facilitating efficient product transit and permitting the mobility of people for employment, education, and tourism, it promotes commerce, improves connectivity, and supports industries. Assessing the economic effect, doing cost-benefit evaluations, and fostering economic development via transportation improvements are all included in the scope.

The paper is structured as follows: Related works presents in part 2, proposed method presents in part 3, Result and discussion presents in part 4, and part 5 presents in summary of the study.

Contribution of the paper:

- The collected dataset was pre-processed using z-score normalization, then independent component analysis (ICA) was applied for the feature extraction process.
- Real-time monitoring enables the detection of anomalies and delays, providing alerts for timely actions.
- Overall, GD-KNN empowers transportation logistics monitoring to optimize operations, enhance customer service, and reduce costs in transportation systems.

2. Related works

The study by Haydari and Yılmaz[9] covered the most recent uses of Deep Reinforcement Learning (DRL) for traffic management. The focus of the discussion is on Traffic Signal Control (TSC) applications based on deep RL, which has received a great deal of attention in the field of research. The various RL parameters, simulation, and issue formulation settings for TSC are thoroughly described. Deep RL models have been used to study a number of autonomous driving applications in research. The article Making a safe energy trading environment that can be utilized for functions like charging and discharging from the underlying smart grids is one of the key challenges in the context of autonomous vehicles, such as unmanned aerial aircraft and electric (ground) vehicles. Internet of Things (IoT) rising technological trend age is the tactile internet, which has the potential to be used in a wide variety of commercial, social, and industrial use cases. The goal of this article by Zantalis et al.[10] is to offer a summary of ML methods and IoT applications in ITS, as well as to identify any potential coverage gaps and get a clear understanding of the prevailing trends in the aforementioned disciplines. It is clear from the examined literature that ML may not be sufficiently covered for applications like smart parking and lighting systems. Furthermore, among academics, the most common ITS applications are route optimization, parking, and accident/detection.

The study by Poornima et al.[11] suggested approach has two features. First, the research of automated fog-robotics transport system for energy management includes decentralized wireless sensor transfer-aided flocking self-driving. It displays the sensor operations as they relate to roadside meter scanning. In it, speed control is listed. Second, on the basis of Vehicle Infrastructure Integration (VII), intelligent speed assistance powered by artificial intelligence is created. Using this integration of the automotive infrastructure, the smart highway may be modified to work with robotic fog systems. The paper by Deveci et al.[12] offered a hybrid decision-making paradigm for q-ROFS context-based prioritization the Metaverse's sustainable transportation system. In order to aggregate the q-ROF information, initially, Dombi weighted aggregation operators with q-ROF generalization and their features are constructed. It is recommended to use a q-ROF information-based method in order to determine the objective and subjective weights of criteria by using models of stepwise weight assessment ratio analysis and the effects of removing criterion. The study by Tan et al.[13] determined managing transportation networks in the presence of electric vehicles (EVs) that support dynamic wireless charging (DWC) is reviewed and projected in this article. DWC, which is based on the concept of coupling inductively, enables EVs will charge wirelessly by driving past coils hidden in the ground. DWC is often referred to as driving while charging or charging while moving, and it is one of the most hopeful methods for charging EVs. The term wireless charging lane (WCL) refers to the section of the road having wireless chargers installed underneath its surface.

Traffic congestion may be found via a clustering study using the Parallel Social Spider Optimization (PSSO) approach[14]. The decision to use the PSSO method was influenced by earlier findings in which it was contrasted to the K means and Social spider optimization algorithms for resolving clustering issues. The study by Humayun et al.[15] intended to advance the area of transportation and logistical support by investigating the possibilities of smart logistics and transportation using blockchain and IoT. In order to create an intelligent logistics and transportation structure, they offer the BCTLF, a layered architecture that combines IoT and Blockchain. The study by Ouyang and Wang[16] determined a vehicle recognition method based on the YOLOv3 (You Only Look Once) model that was trained using a significant amount of traffic data proposed. In order to guarantee the model's performance on cutting-edge hardware, they trimmed it. The Deep Simple Online and Real-time Tracking (DeepSORT) method is then improved by retraining the multi object vehicle feature extractor monitoring. After that, they suggest vehicle tracking in real-time counters for cars that incorporates methods for locating and tracking vehicles to enable traffic flow monitoring. The study by Tsyganov[17] proposed the establishment of a union for multimodal transportation and logistics and provided a macro-level plan for its cutting-edge infrastructure. The inadequate formalizability of the quality-of-logistics-services-parameters and the customers' subjective judgments of service quality makes it difficult to apply the strategy of minimizing overall logistics expenses. The study by Casado-Vara et al.[18] suggested a method that leverages smart contracts to cut out middlemen and quicken logistical operations. Additionally, a multi-agent system is employed to manage smart contracts, complete logistical services, and adherence to their requirements. The article by Arslan et al.[19] provides a wide overview of current developments in anomaly detection based on a thorough study. Efforts have been made to go into recently published research in order to uncover cutting-edge methods that hold promise for the future. As such, we have reviewed the relevant literature on anomaly detection systems in network traffic, with a range of common uses including WSNs, the Internet of Things (IoT), HPC, ICS, and SDN settings.

3. Materials and methods

This section discusses applying machine learning to monitor transportation logistics for the transportation system. Monitoring systems for transportation logistics collect real-time data from vehicles, infrastructure, and other pertinent sources using technologies like GPS, sensors, telematics, and communication networks. To get useful insights and make wise choices, this data is then processed and analyzed using a variety of tools and methods, including machine learning and data analytics. The goal of the suggested method is to show how the K-Nearest Neighbors algorithm and Gradient Descent work synergistically to greatly increase the accuracy as well as efficiency of transportation logistics optimization. It is a potential approach for real-world transport systems, and experimental results will be provided to demonstrate the performance advantages realized in terms of decreased user cost time and enhanced customer service. The suggested procedure flow is shown in **Figure 1**.

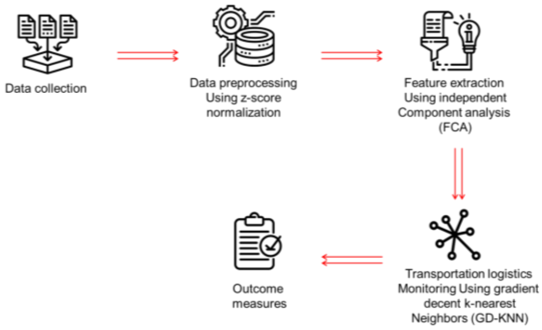

Figure 1. Flow diagram.

3.1. Data collection

The study aimed to gather information from road freight transportation businesses in Poland's south using a key informant approach. The target audience consisted of management staff, with the presidents, directors, and IT managers having the most expertise in assessing logistical resources, ITS applications, and customer service logistics. An inquiry form was created, and 267 representatives of road freight transport were interviewed over the phone using a computer program. The industry was placed over three months from September to November 2020. Out of the information gathered, 103 questionnaire data were incomplete or incorrect, and 164 interviews with business entity representatives produced the fundamental study data.

The most important section of the questionnaire was created to gather data on all the model's variables, and there were six portions in it: ITS programs for vehicle promote ITS applications in road freight transport businesses for common leadership in such logistics data, enterprises, logistics customer service, and logistics knowledge. In addition, the inquiry form included questions on the essential characteristics of the business organizations, which clarifies the findings shown in **Table 1**.

Table 1. Basic characteristics of the responsive businesses.

Attribute	Share	Reaction
Progress in using the ITS application	10.5% 79.11% 10.9%	Advanced Intermediate Beginner
Age of business activity	17.2% 56.2% 24.3% 3.7%	Less than 3 years 3–8 years 9–19 years 20 years or more
Region of business activity	6.8% 73.2%	Domestic International
Predominant business profile	67.1% 28% 4.9%	Transportation Shipping Third-party logistics

3.2. Using Z-score normalization for data preparation

Z-score normalization begins with the mean and standard deviation of the data. The approach can be effective when the lowest and maximum values of the data are unknown. The formula in use is this one:

$$Z_{new}=\frac{Z-\mu}{\sigma}=\frac{Z-Mean(z)}{stdDev(z)} \tag{1}$$

Z_{new}=The adjusted value obtained after scaling the data; Z=outdated value; μ=Statistics mean; σ =Estimated Standard Deviation.

3.3. Using ICA to extract features

Analyzing independently of components. Multivariate random signal is converted into another kind of feature extraction via ICA. A signal with independently interacting parts. It is presumptive that the number of measured signals and independent signals is equal and that each measurable signal is a linear synthesis of all individual signals. Suppose we see n linear combinations of the kind $v_1, \dots, v_n$. The mixes are a linear fusion of n different parts.

$$v_i = b_{i1}t_1 + b_{i2}t_2 + \cdots + b_{im}t_m \tag{2}$$

Where t_l ($l = 1\ ton$) represents the separate parts that we are seeking, we may assume with no loss of generality that the independent elements and mixing variables both have zero means. We can use the vector notation to all to ow$v$ show combinations v1on s$v_1, v_2, \dots, v_n$. Here t represents the separate elements. The collaborating model is stated as if the mixing matrix is designated as "B"$v = Bt$. The Independent Component Analysis model is used in this. Once the matrix B has been estimated, the inverse of the matrix U may be calculated, and the independent components can be identified as$t = Ut$

3.4. Gradient descent k-nearest neighbors (GD-KNN)

An optimization technique called gradient descent is used to reduce a model's cost function. It is often used to train machine learning models, particularly those based on neural networks or regression. The cost function's negative gradient is used by the method to incrementally update the model's parameters. The K-Nearest Neighbours approach is a simple but effective option for classification and regression issues. The K closest neighbors in the training dataset are used to compute the projected value for a new data point in KNN, either by majority vote (for classification) or average.

The GD-KNN approach is suggested to identify the k training samples that are closest to the target object in the training set. Assign the dominating category to the target item after identifying it from the k training examples, where k is the number of practice samples. Accordingly, the main working principle of the GD-KNN method is that every sample has the same features when they are grouped together; which category, in a feature area, falls under the same heading comprises the samples that are k most closely related to each other. Only the category of the closest one or more samples is used by the approach to determine which category the sample falls into when making the classification decision. In addition, only a very limited number of nearby decision-making examples in several categories are significant to the GD-KNN method. The GD-KNN algorithm is better suited than additional forms for the remaining sample sets with higher overlap or cross-class domains because it relies primarily on the nearby constrained neighboring samples as opposed to using the discriminant domain method to determine the category. **Figure 2** illustrates the concept behind the GD-KNN method. when the one neighbouring sample belongs to $\omega 3$, and four neighbouring samples belong to($\omega 1$), Xu falls into category $\omega 1$.

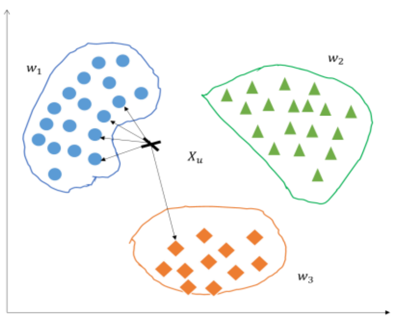

Figure 2. K-NN proximity algorithm map.

The gradient descent K-NN Algorithm 1 described implementation procedure consists of the following six steps:

Algorithm 1 Gradient Descent K-NN algorithm

1: Choose the value of k.
2: Determine the separation between the current point and the point in the known category data set.
3: Sort the data in ascending distance order.
4: The k points with the closest distance to the present position should be chosen.
5: Identify the category where k points are located occurrence frequency.
6: Return to the anticipated categorization of the current point, which is the category with the greatest probability of recurrence among the first k points.

In order to choose the nearest k labeled data$\{z_1, z_2, \ldots, z_k\}$, the projected data point's distance based on a given data point must first be calculated using the K-NN method. Here, z_1 stands for the known data point that is nearest to the forecasted point, z_2 stands for the predicted data point that is the second-closest known data point, and so on. Thus, Equation (3)'s K-NN method regression may be used to anticipate short-term demand.

$$T_j = \frac{1}{k} \times \sum_{i=1}^{l} t_{z_i} \tag{3}$$

where T_j is the j^{th} predicted value, which is the mean of $t_{z_i}(i = 1,2, \ldots, k)$; t_{z_i} a projected value for thej^{th}nearest available data pointz_i.

4. Results and discussion

The GD-KNN machine learning algorithm is used to monitor the transportation logistics for the transportation system in this section. The suggested approach compared many approaches, including the RCNN[20], the ANN[21], and the LSTM[22]. The suggested strategy is accomplished by looking at factors such as speed, efficiency, cost reduction, and accessibility. The proposed approach looks at accuracy, precision, recall, F1-score, speed, efficiency, cost-reduction and accessibility, with other factors.

4.1. Analysis of speed

A capacity and throughput of the transportation system are directly impacted by the speed at which vehicles move on roads, trains, airways, and waterways. Faster delivery, shorter travel times, and more efficiency are often the outcomes of higher vehicle speeds. However, there are regulations on vehicle speed restrictions for safety reasons, and each form of transportation has its own unique speed limits. **Figure 3** and **Table 2** denote the speed of the proposed and existing methods. And the network speed is the rate at which data and information are transported throughout the communication network of the transportation system. For smooth data interchange, stakeholder communication, and real-time tracking, fast and dependable network speeds are essential. Rapid decision-making, reduced information lag and effective logistical management are all made possible by high-speed networks.

Table 2. Outcomes of the speed.

Dataset	Speed (%)			
	RCNN	ANN	LSTM	GD-KNN [Proposed]
1	87	91	89	93
2	82	89	87	91
3	85	83.2	89.9	92
4	85	82	87	90
5	87	91	89	93.3

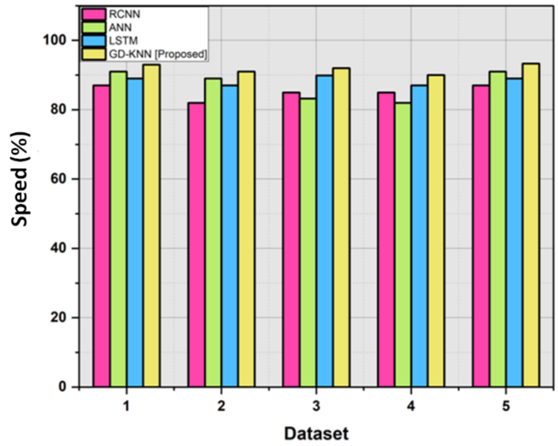

Figure 3. Speed of the proposed and existing methods.

4.2. Accessibility

The qualities and traits that affect how easily people with different requirements may use transportation services and whether they are available are referred to as accessibility parameters in a transportation system. In order to make transportation services physically accessible to individuals with disabilities or mobility issues, infrastructure, and facilities must be put in place. For those who are visually impaired, this includes amenities like ramps, elevators, accessible parking places, wide entrances, and tactile pavement. Physical accessibility guarantees that transportation hubs, stops, and vehicles are barrier-free and usable by anyone with a range of physical abilities. **Figure 4** shows the accessibility of the proposed and existing methods. The accessibility of transportation networks for people with wheelchairs is crucial. It entails providing wheelchair users with specific places, securement systems, ramps, or elevators for boarding and alighting from vehicles. **Table 3** shows the results of accessibility.

Table 3. Result of the accessibility.

Dataset	Accessibility (%)			
	RCNN	ANN	LSTM	GD-KNN [Proposed]
1	89	87	90	93
2	83	89	87.2	91
3	87	82	89.5	92
4	88	85	87	90
5	87	82	89	95.4

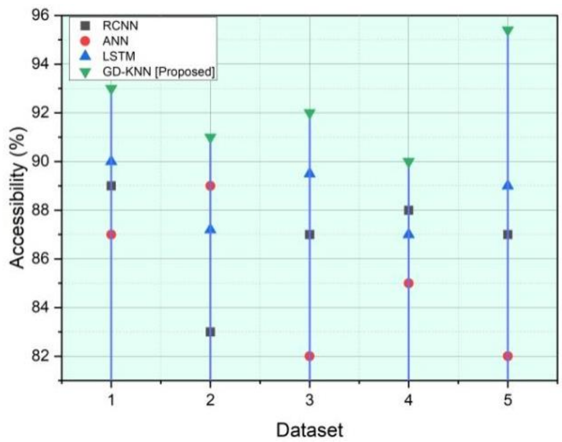

Figure 4. Accessibility of the proposed and existing methods.

4.3. Efficiency

The characteristics and indications that define a transportation system's efficacy and productivity in terms of resource utilization, time management, cost-effectiveness, and overall performance are referred to as efficiency parameters. These variables aid in evaluating and enhancing the effectiveness of transportation operations. **Figure 5** denotes the efficiency of the proposed existing methods. The typical occupancy or use of cars within the transportation system is represented by the vehicle load factor. In transportation systems, fuel economy is a key factor, particularly for fossil fuel-powered vehicles. It calculates the amount of gasoline used for every unit of cargo or distance moved. **Table 4** denotes the outcomes of the efficiency. Reducing fuel costs, minimizing environmental effects, and enhancing the sustainability of transportation operations may all be achieved by increasing fuel economy via strategies including vehicle maintenance, route optimization, and eco-friendly technology. Efficiency encompasses a holistic evaluation of an optimization method, considering both computational efficiency and the effectiveness of achieving transportation logistics goals. GD-KNN, with its dual focus on optimization and prediction accuracy, will be compared with existing methods to determine which strikes the best balance between efficiency and effectiveness.

Table 4. Outcomes of the efficiency.

Dataset	Efficiency (%)			
	RCNN	**ANN**	**LSTM**	**GD-KNN [Proposed]**
1	87	92	89	94.3
2	89	87	91	93.5
3	93	89	90	95
4	87	86	89	92
5	89	93	90	96.6

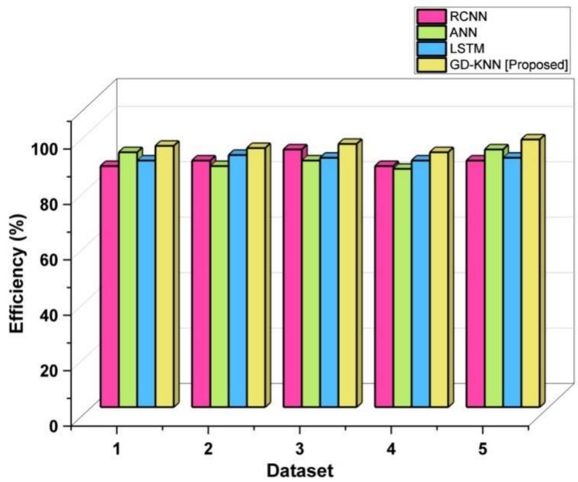

Figure 5. Efficiency of the proposed and existing methods.

Costs associated with logistics monitoring may be considerably decreased by using automation and utilizing technology. Automation eliminates the need for human intervention and related labor expenses by collecting and processing data, creating warnings, and carrying out regular operations. Logistics managers may optimize routes to cut down on mileage, fuel use, and idle time by using cutting-edge routing algorithms and real-time traffic data. Improved client satisfaction and quicker delivery times are additional benefits of optimized routes. **Figure 6** demonstrates the cost reduction of the proposed and existing method. **Table 5** demonstrates the result of cost reduction. Through its optimization capabilities, the GD-KNN technique seeks to minimize delays, optimize route planning, and reduce total operating costs. A comparison with other ways will reveal which method gives the most substantial cost reductions across several situations, including fuel economy and maintenance expenses.

Table 5. Result of the cost reduction.

Dataset	Cost reduction (%)			
	RCNN	**ANN**	**LSTM**	**GD-KNN [Proposed]**
1	70	67	61	52
2	63	64	55	54
3	60	63	68	51
4	63	75	62	55
5	65	72	60	50.2

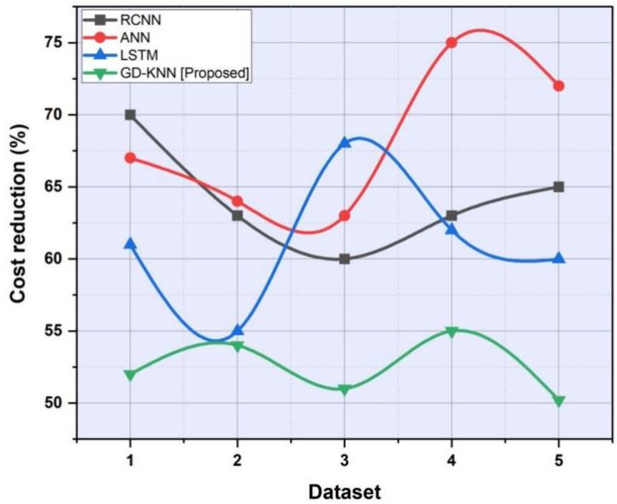

Figure 6. Cost reduction of the proposed and existing methods.

A metric's accuracy is its capacity to accurately and properly represent a system's performance across every course. If each class is given the same weight, then everyone wins. The value is computed as a percentage of the total number of recommendations and true statements as shown in **Figure 7** and **Table 6**.

$$Accuracy = \frac{T_{positive} + T_{Negative}}{T_{positive} + T_{Negative} + F_{positive} + F_{Negative}} \quad (4)$$

The amount of accurate class predictions produced from a given sample is known as precision. Stated differently, it makes a comparison between the actual and expected results. Apply this formula to ascertain an observation's accuracy: When comparing proposed method GD-KNN of accuracy and precision obtain 98% and 97% respectively.

$$Precision = \frac{True\ positive}{Total\ predicted\ positive} \quad (5)$$

Table 6. Result of the accuracy and precision.

Methods	Percentage (%)	
	Accuracy	**Precision**
RCNN	91	85
ANN	94	87
LSTM	89	91
GD-KNN [Proposed]	98	97

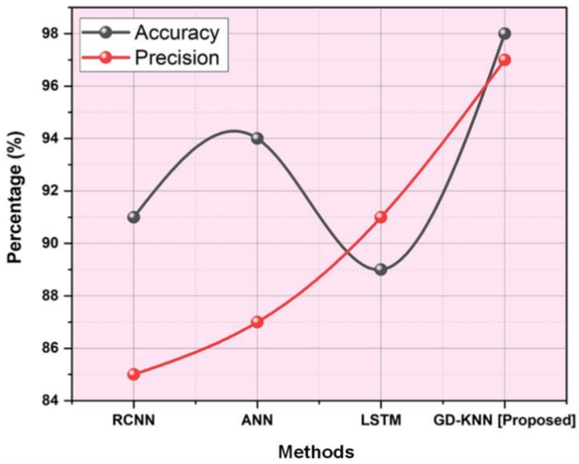

Figure 7. Compare with accuracy and precision of the proposed and existing methods.

The efficiency with which medical imaging information systems are able to find the relevant supplementary data for the insurance plan and stock price is measured using a metric known as recall. It has been shown that the following processes are essential:

$$Recall = \frac{True\ positive}{total\ number\ of\ actual\ positives} \tag{6}$$

The F1 score also takes accuracy and recall into effect. A statistical metric that shows the midway between datasets is the frequency mean. Sometimes using contemporary techniques for number averaging is a preferable option when working with ratios because of the latency involved in using traditional statistical distributions as shown in **Figure 8** and **Table 7**. When comparing proposed method GD-KNN of recall and F1-score obtain 95% and 92% respectively.

Table 7. Result of the recall and precision.

Methods	Percentage (%)	
	Recall	**F1-Score**
RCNN	91	85
ANN	80	79
LSTM	85	90
GD-KNN [Proposed]	95	92

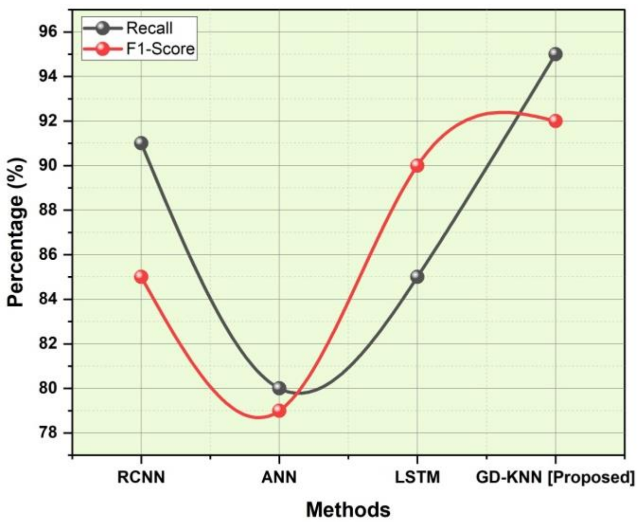

Figure 8. Compare with Recall and F1-score of the proposed and existing methods.

4.4. Discussion

Gradient Descent combined with the K-Nearest Neighbors (GD-KNN) technique for transportation logistics optimization is a workable solution to the numerous challenges this complex area offers. Significant aspects including accuracy, precision, recall, F1-score, cost reduction, speed, accessibility, and efficiency are thoroughly discussed when GD-KNN is contrasted with other machine learning techniques now in use. GD-KNN effectively optimizes transportation logistics via the use of two potent techniques: gradient descent and K-nearest neighbors. It's an attractive alternative because of its ability to adapt to non-linear interactions, efficient feature scaling and normalization, dynamic hyper parameter modification, and computing efficiency optimization. The decision to use GD-KNN over other existing techniques will ultimately come down to empirical validation across a range of conditions. Based on its performance and practical applicability in various logistics scenarios, GD-KNN's suitability for real-world transportation logistics optimization will be determined. Sectors seeking increased productivity, reduced costs, and improved logistical decision-making are finding that GD-KNN offers a promising answer to the intricate difficulties of transportation optimization.

5. Conclusions

The nearest neighbor distance technique was used in this study to provide the suggested approach with the proper weights for each data point. It is discovered that the suggested GD-KNN model has greater speed and effectiveness by the diverse sample's verification and analysis. For instance, power consumers may develop effective plans for energy-saving renovations based on the evaluation's findings, which would ultimately increase electricity efficiency. The ability of the suggested GD-KNN model is much superior to these other existing models when compared to the present model. In comparison to current techniques RCNN, ANN, and LSTM, the suggested approach achieves superior efficiency (96.6%), accessibility (95.4%), cost reduction (50.2%), and speed (93.3%). Utilizing the potential of cutting-edge data analytics methods will determine the direction of transportation logistics monitoring in the future. Logistics managers may obtain deeper insights from the enormous quantity of data created in the transportation system by using artificial intelligence, machine learning, and predictive analytics.

Author contributions

Conceptualization, SKG and MSY; methodology, CP; software, DC; validation, RS, RRC and KKG; formal analysis, RS; investigation, CP; resources, DC; data curation, RRC; writing—original draft preparation, SKG; writing—review and editing, MSY; visualization, RRC; supervision, CP; project administration, SKG. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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