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Intelligent Transportation System's Machine Learning-Based Traffic Prediction

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Abstract

The aim of this study is to develop an accurate and timely traffic flow prediction tool that considers various factors influencing road conditions, such as road repairs, rallies, traffic signals, and other everyday events that can impact traffic movement. By providing drivers with near real-time predictive insights, they can make more informed decisions, enhancing traffic management and potentially supporting future autonomous vehicle technologies. Given the exponential growth in traffic data, this research applies big data principles to the transportation domain, where existing traffic prediction models struggle to handle real-world applications effectively. In this study, we implemented machine learning, genetic algorithms, soft computing, and deep learning techniques, achieving a traffic flow prediction accuracy of 93.5%. The results demonstrate a significant improvement in prediction accuracy compared to conventional models, which typically average around 85%. Additionally, image processing algorithms for traffic sign identification are integrated, achieving 90% accuracy in identifying key traffic signs, further aiding in the training of autonomous vehicles. The proposed approach addresses the challenges posed by large-scale transportation data, offering a solution with improved predictive accuracy and practical utility.

Keywords: Big Data, Soft Computing Genetic Algorithms, Deep Learning, Machine Learning, Traffic Environment, Process Innovation, Public Infrastructure, Image Processing

1. Introduction

Accurate traffic flow information is essential for various sectors, including business, government, and individual travelers. It helps reduce congestion, enhance traffic operation efficiency, and lower carbon emissions, empowering drivers and passengers to make more informed travel decisions. The development and adoption of Intelligent Transportation Systems (ITSs) have significantly improved traffic flow prediction accuracy, making it a critical component in the operation of traveler information systems, advanced public transportation networks, and sophisticated traffic management systems [1].

Traffic flow prediction relies on both historical data and real-time traffic information, which is collected from diverse sources such as social media, inductive loops, radars, cameras, mobile Global Positioning Systems (GPS), and crowdsourced data. With the increasing use of both traditional and modern sensors, traffic data volume is expanding exponentially. This influx of data is transforming the way transportation is managed and controlled, leading to data-driven solutions [2], [3].

Despite the existence of numerous traffic flow prediction models, many of them are limited by simplistic methodologies and struggle to process large datasets effectively. Recently, Deep Learning (DL) techniques have gained attention for their ability to tackle complex problems such as classification, natural language understanding, dimensionality reduction, object recognition, and motion modeling. DL methods employ multi-layer neural networks to extract insights

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from data across multiple levels, uncovering underlying patterns that improve visualization and decision-making [4]. The potential of these techniques extends to the development of autonomous vehicles, which promise to reduce transportation costs and human casualties while saving time. Safe automated driving, including systems like driver assistance systems (DAS), autonomous vehicles (AV), and traffic sign recognition (TSR), has become a focal point of research in recent decades [5].

While numerous algorithms, including genetic algorithms, machine learning, deep learning, and soft computing, have been proposed for traffic flow prediction, many still face challenges in providing accurate predictions with manageable complexity. Achieving precise traffic flow forecasting remains a difficult task, particularly when large-scale data is involved.

2. Literature Review

ITS encompass several key domains that contribute to efficient traffic and transportation management. Motorway and Arterial Management Systems focus on optimizing vehicle flow on highways and major roads through technologies like traffic signals and real-time data from sensors. Transit Management Systems (TMS) enhance public transportation by enabling real-time tracking, dynamic scheduling, and providing timely passenger information for smoother operations. Incident Management Systems ensure quick detection and response to traffic disruptions caused by accidents or breakdowns, coordinating efforts between emergency services and traffic control centers to minimize delays. Lastly, Information Management (IM) and the Transportation System collect, process, and disseminate real-time data such as traffic updates and weather conditions, helping commuters make informed decisions and supporting long-term transportation planning.

2.1. Motorway and Arterial Management Systems:

Traffic congestion is becoming an increasingly significant issue globally. Its several reasons include a growing population, inadequate infrastructure, and an ineffective transportation system. Many transportations related agencies employ the highway and arterial management systems to address this issue. The Las Vegas transit is controlled and monitored by the system installed and used in South Nevada (RTS) [6]. The California Motorway Management technology is another illustration of this type of technology. This system handles 2 Gb/day of data in real time [7]. Millions of raw data points, including traffic flow, speed records, and other information, are collected and stored in these systems. Traffic signal control systems, ramp meter circuit television (CCTV), variable message signs (VMS), and other cutting-edge hardware are used in the system's operation. The use of mobile phones, GPS, and portable sensors has increased recently. The studies compare GPS-based sensors with mobile-based sensors. Due to their widespread coverage and readily available infrastructure, mobile-based sensors are more effective [8], [9]. Bluetooth traffic monitoring systems are recommended as a replacement for loop detectors and can measure their accuracy.

2.2. Transit Management Systems (TMS):

TMS provides precise data regarding the location, happiness, safety, and security of passengers. The Transit Management System improves response times to service interruptions, operating efficiency, and ridership. The user or passenger has the right to use the data while travelling via various devices, at home, at work, at a transportation hub, at wayside stops, or within the car. Maps, operational information, schedule information, and general information are all included in this information. Vehicle tracking is made possible using Automatic Vehicle Location (AVL) technology, which is an example of a transit management system. In addition to giving travelers information about the whereabouts of transit vehicles, AVL offers real-time position data from vehicles that are used to verify schedule adherence. A variety of software programs, such as AVL, Bus Rapid Transit (BRT), and Travel Assistant Device (TAD), are used in the transit management industry to improve location and transit time, as well as to support safety operations. Incident management sectors are also expanding technologically [10].

2.3. Incident Management Systems:

An important component of intelligent transportation systems is incident management. Transit plays a significant role in emergency situations and in traffic accidents. For example, during various crises such as the SARS virus, the 2008 Sichuan earthquake, or the September 11 attack, one of the key goals in these instances is to trace the safe route to our destination using fire trucks and ambulances. Data from the World Health Organization show that accidents and injuries are a significant public health concern in Europe, where the annual death rate is approximately 31,000. Over 1.2 million people pass away on global roadways, and the WHO predicts that by 2030, transportation-related injuries will rise to become the fifth most common cause of death. Roadway incident management, emergency response management, incident detection, and traffic management are only a few of the several subsystems that make up an event management system [11].

2.4. Regional Multimodal and Traveler Information System:

The primary hub for gathering data on roads and transport is the Regional Multimodal and Traveler Information System (also known as Information Management, or IM). This system includes all kinds of roads, transportation, motorways, and arterials that connect all locations, including nearby cities and nations. The system is raising the standard of real-time information gathering, accessibility for travelers, and data collection overall. It is also used for route planning, real-time transportation, traffic and transit scheduling, and parking. Travelers can easily and profitably obtain information from a single platform in real time with the help of regional multimodal and travel information systems [12]. Wireless and online technologies are integrated in Regional Multimodal and Traveler Information Systems. Transportation planning, design, modelling, analysis, and management are made more efficient by information management systems, which also help to avoid delays.

2.5. Applications of Intelligent Transportation Systems:

ITS have a wide range of applications aimed at enhancing transportation services, safety, and operational efficiency. One significant application is Electronic Toll Collection (ETC), which streamlines toll payment processes by allowing vehicles to pass through toll points without stopping, using electronic sensors and payment systems. This reduces congestion and improves the overall flow of traffic in toll areas. Another key application is Highway Data Collection (HDC), which involves gathering real-time traffic data from various sources, such as sensors and cameras, to monitor highway conditions and provide timely information for traffic management and planning.

Additionally, TMS are crucial for optimizing the flow of vehicles on roads by using technologies such as traffic signals, surveillance cameras, and sensor networks to manage congestion and improve road safety. Vehicle Information Detection (VID) systems collect data related to vehicle performance and behavior, such as speed and fuel consumption, providing valuable insights for both drivers and transportation authorities to enhance safety and efficiency.

Transit Signal Priority (TSP) is another important ITS application, which gives public transit vehicles, like buses and trams, priority at traffic signals to reduce delays and improve service reliability. Lastly, Emergency Vehicle Preemption (EVP) systems allow emergency vehicles, such as ambulances and fire trucks, to override normal traffic signals, ensuring they can quickly and safely reach their destinations during emergencies, thereby reducing response times and improving public safety.

2.6. Intelligent Transportation System Technologies:

The Intelligent Transportation System combines the state of modern and developing communication technology. Because of the advent of numerous technologies, including the transportation system can enhance the quality of transportation, services, and safety. Communication via wireless Technologies that compute Data from floating cars and floating cellphones methods for sensing discovery of inductive loops video detection of moving vehicles Bluetooth identification.

ITS was approved during the 1994 World Congress in Paris. To improve traveler information and boost the effectiveness and safety of road transport systems, the ITS has applied computer, electronics, and communication technologies. ITS's primary benefit is its ability to facilitate safe and efficient road transport. Reducing carbon emissions is beneficial from an environmentally friendly standpoint as well. As seen in figure 1, it offers numerous chances for the automotive or vehicle companies to improve the security and safety of their passengers [13].

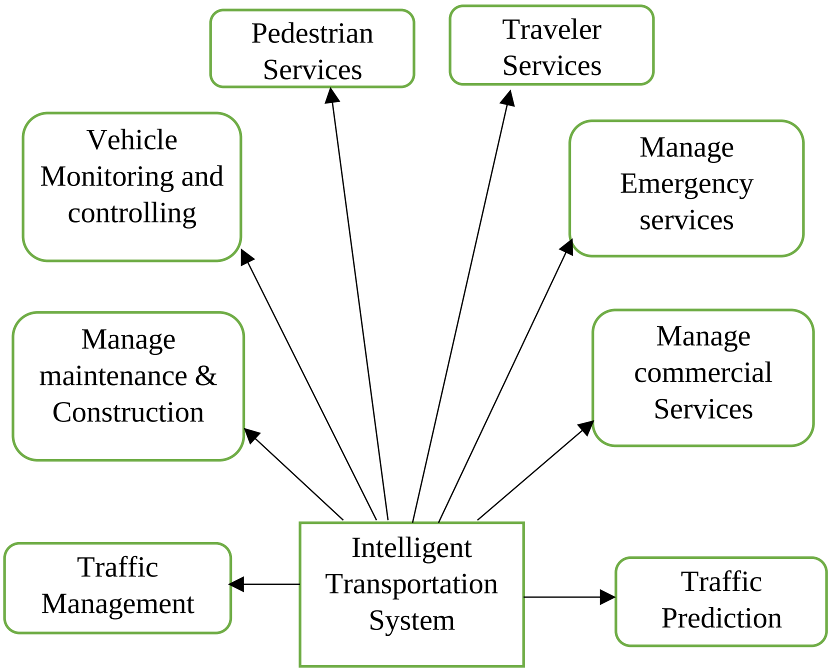

Figure 1. A transportation system with intelligence can do a variety of functions

Regardless of the number of vehicles on the road, traffic also rises. Furthermore, this large load cannot be supported by the capacity of the current road network. There are two ways to go about fixing this problem. Creating more highway lanes and roads is the first step towards ensuring that automobiles can operate smoothly. Its upkeep necessitates large amounts of land and sophisticated infrastructure, which drives up the expense. The network occasionally experienced several issues, such as in an urban region. It is not possible to expand the roads and lanes on this property facility. The second strategy makes effective use of the current road network by implementing a few control mechanisms [13]. These control tactics also result in lower expenses, making them economical models for the government or traffic controllers. The tactics used in this control point out possible traffic jams and advise travelers to choose alternate routes to go where they're going [14].

One useful method for managing a lot of data is deep learning, which is a component of machine learning algorithms. DL offers a way to incorporate intelligence into wireless networks with intricate radio data and expansive topologies. Use neural network concepts in DL. This feature helps identify network dynamics (e.g., spectrum availability, congestion points, hotspots, traffic bottlenecks) [15]. Accurately forecasting travel times is crucial for the development of ITS. Support vector machine (SVM) is one of the most efficient classifiers among somewhat linear ones. Preventing data overfitting has benefits. For comparatively small data sets with few outliers, SVM works well. Although they require more data, other algorithms (Random Forest, Deep Neural Network, etc.) consistently provide very reliable models. Alternatively, SVM fits both linear and nonlinear regression, which we might call support vector regression, by attempting to fit the most significant paths between two classes with the least amount of margin violation. Support Vector Regression (SVR) attempts to minimize margin violations while fitting the greatest number of examples on the route [16].

3. Methodology

This research employs a combination of machine learning algorithms, genetic algorithms, deep learning techniques, and image processing algorithms to predict traffic flow in an intelligent transportation system. The goal is to create a traffic flow prediction model that is both accurate and scalable, suitable for processing large datasets. The methods used are designed to handle the complexity of large data sets while providing timely and accurate predictions. Given the volume of traffic data available today, it is essential to process and analyze this information efficiently. The combination of traditional machine learning techniques with more advanced deep learning models allows the system to manage data effectively and improve predictive accuracy. The integration of image processing for traffic sign recognition enhances the system's usability in autonomous vehicle systems.

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3.1. Data Collection

Traffic data is collected from diverse sources, including social media, inductive loops, radar, mobile GPS, and crowdsourced data. These sources provide a comprehensive view of both historical traffic information and real-time updates. The combination of these data types allows for more accurate predictions of traffic patterns, as it includes not only current conditions but also factors that might affect future traffic flows, such as roadwork or special events. Once collected, the data undergoes a rigorous cleaning process to eliminate noise and irrelevant information. This process ensures that the data used in model training is of high quality, which is essential for developing reliable predictive models. Any missing values or anomalies detected in the dataset are handled using imputation techniques or removed entirely if deemed necessary.

3.2. Algorithm Selection

Several machine learning and deep learning algorithms are used in this study to develop traffic prediction models. The algorithms evaluated include Decision Tree, SVM, KNN, and Modified Random Forest. Each of these algorithms has unique strengths in handling different types of data and performing specific tasks, making them suitable for complex traffic datasets. Decision Tree algorithms, for instance, are ideal for classification tasks where clear decision boundaries are needed. SVM is useful in high-dimensional spaces, preventing overfitting while handling smaller datasets efficiently. KNN provides a simple yet effective method for classification by analyzing the nearest neighbors, and the Modified Random Forest algorithm is employed to enhance model accuracy when dealing with larger datasets.

3.3. Model Training and Evaluation

The traffic prediction models are trained using a labeled dataset. Each model's performance is evaluated based on several metrics, including accuracy, precision, recall, and processing time. The use of cross-validation ensures that the models are robust and generalize well to unseen data, thus avoiding the risk of overfitting, which could compromise prediction accuracy. The evaluation process also includes identifying and handling outliers. These are data points that deviate significantly from other observations, which can distort the model's performance. SVM are used in this phase to detect outliers and ensure that the models trained are not adversely affected by these anomalies. This process enhances the reliability of the predictions produced.

3.4. Traffic Sign Recognition

In addition to predicting traffic flow, image processing algorithms are employed for traffic sign recognition. This feature is crucial for the future integration of autonomous vehicle technologies, as it allows vehicles to interpret and react to traffic signs accurately. The traffic sign recognition system is trained using a large dataset of traffic signs, ensuring it can recognize and classify signs correctly even in challenging conditions. By integrating traffic sign recognition into the broader traffic prediction system, the model improves its ability to provide comprehensive driving assistance. This functionality is especially useful for autonomous vehicles, where accurate traffic sign interpretation is key to safe driving. Image processing techniques enhance the precision of this system, making it highly effective in real-world applications.

3.5. Implementation Tools

The traffic prediction models are implemented using Python, along with key libraries like sklearn, which provide tools for machine learning model development. Android Studio and Java are utilized for the development of the user interface and application, which allows users to access traffic predictions in real time. This mobile application is designed with a simple interface, ensuring ease of use and quick access to predictions. The application also integrates real-time data feeds, enabling it to display traffic conditions as they evolve. This functionality is critical for drivers and autonomous vehicle systems, as it allows them to make informed decisions based on the most current traffic information available. The mobile application, therefore, serves as the bridge between the traffic prediction model and its practical application for end-users.

3.6.System Architecture

The system's architecture comprises three main components: data input, machine learning model processing, and output delivery via a mobile application. The architecture is designed to handle both real-time data streams and historical datasets, providing accurate traffic predictions that are both timely and relevant to current conditions. The data processing pipeline ensures that the traffic data is processed and analyzed efficiently, delivering predictions quickly to the user. The mobile application offers a user-friendly interface where drivers or autonomous systems can access traffic predictions and recommendations. This allows for real-time decision-making, helping users avoid congested areas or adjust their routes based on predicted traffic flow. By integrating traffic sign recognition and traffic prediction models, the system provides a comprehensive solution for both manual and autonomous driving environments.

4. Requirement Specifications

Android Studio, Java, Garmin, PHP, XML, Python, and the sklearn library are utilized to achieve the paper's goals. The program was designed with the minimal buttons to ensure that users could operate it without difficulty. In order to ensure that the application loads quickly and doesn't cause the user any trouble, the interface is also kept simple. A Toast View displays the application's geo coordinates. The application's screen grab is plainly visible in figure 2, where it is evident that the interface has been kept simple.

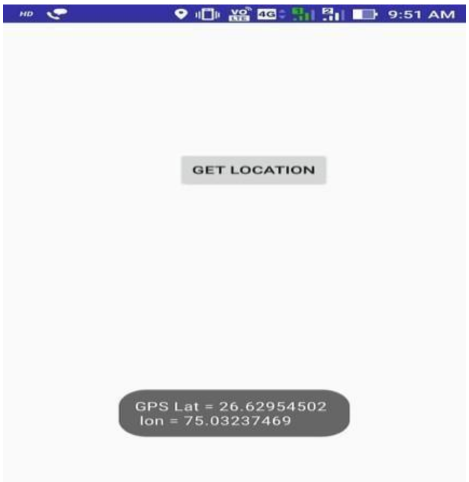

Figure 2. An image of the application's screen

Provide a statement that what is expected, as stated in the "Introduction" chapter can ultimately result in "Results and Discussion" chapter, so there is compatibility. Moreover, it can also be added the prospect of the development of research results and application prospects of further studies into the next (based on result and discussion).

5. Application and Outcomes

Various machine algorithms have been implemented and evaluated to get enhanced efficacy and precision in our findings. Using a Decision Tree Algorithm (DT), we have identified classification and regression. Predicting the target variables' values is the aim of this approach [17]. Decision tree learning is a function that accepts a vector of attribute values as input and outputs a single value called a "Decision." Ii belongs to the class of algorithms for supervised learning. Both regression and classification problems can be resolved with it. By running a series of tests on the training dataset, DT determines its outcomes [18]. Another crucial stage in achieving an accurate result is the detection of outliers. To do this, we have employed Support Vector Machines (SVMs), a collection of supervised learning techniques that are also applicable to regression and classification [19]. When there are fewer samples than there are dimensions, the SVM can be helpful in high dimensional domains [20].

One reliable machine learning approach is the Modified random forest algorithm [21], [22], [23]. As bootstrap aggregation, it is described. The primary purpose of the Modified random forest method, which is based on forecasting models, is data classification. A single training data set can be used to create many models using the bootstrap approach. Conclusion regarding traffic congestion by putting the aforementioned procedures into practice, we can use this method and produce a machine learning model that is more accurate than the ones that are now in use [24].

Using the gradient-based improvement technique in conjunction with the BP methodology makes coaching the deep network simple [25]. However, the networks trained using this technique performs dangerously well. Therefore, using deep learning and genetic algorithms won't be a wise choice because the dataset we have produced is sparsely feature-rich [26], [27]. By using the suggested technique, we have been able to resolve numerous big-data-related concerns and prevent the overfitting of the model by reducing the enormous dataset's dimensions.

6. Results and Discussion

Table 1 presents a comprehensive evaluation of the performance outcomes of various machine learning algorithms based on key metrics, including accuracy, precision, recall, and the time taken for execution. The algorithms compared in this study are Decision Tree, SVM, K-Nearest Neighbors (KNN), and Modified Random Forest. The Decision Tree algorithm achieves an accuracy of 85%, with precision and recall values of 85.56% and 81%, respectively, while completing the task in 94.1 seconds. SVM outperforms the Decision Tree in terms of accuracy and precision, reaching 88% and 86.88%, respectively, with a recall of 84%, but it takes longer to run, requiring 108.1 seconds. KNN shows further improvement, achieving 90% accuracy, 89.88% precision, and 86% recall, though it also takes more time at 111.2 seconds. Among the algorithms, the Modified Random Forest delivers the highest performance, with 92% accuracy, 91.25% precision, and 88% recall. However, it has the longest processing time, requiring 116.2 seconds. This comparison highlights the trade-off between accuracy and processing time, with Modified Random Forest providing the best results at the cost of increased time, while SVM and KNN offer a balance between performance and efficiency depending on the application.

Table 1. Evaluating Boundaries for Various Machine Learning Techniques

Algorithm	Accuracy	Precision	Recall	Time
Decision Tree [22]	85%	85.56%	81%	94.1sec
SVM [23]	88%	86.88%	84%	108.1sec
KNN	90%	89.88 %	86%	111.2 sec
Modified Random Forest	92%	91.25%	88	116.2 sec

Figure 3 provides a visual comparison of the performance of the proposed model against existing machine learning methods, specifically focusing on accuracy, recall, and precision metrics. The current methods included in the comparison are Decision Tree, SVM, KNN, and Modified Random Forest. The figure highlights the performance of the proposed model, which has been evaluated through experimentation. The results indicate that the proposed model demonstrates superior performance in the context of the Decision Tree algorithm. It achieves accuracy, precision, and recall values of 88%, 88.56%, and 82%, respectively. These results show a notable improvement over the standard Decision Tree method, as well as competitive performance compared to other advanced methods like SVM and Modified Random Forest. This suggests that the proposed model offers a more efficient and accurate approach, outperforming the existing algorithms in this specific evaluation.

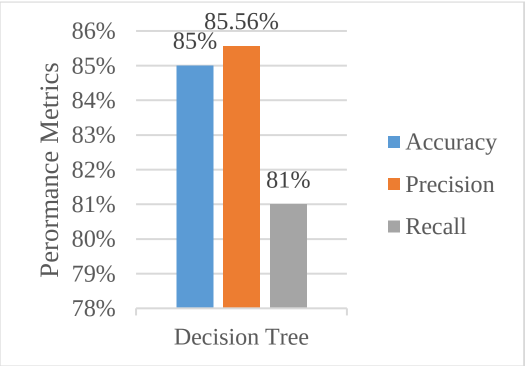

Figure 3. Assessment of Decision Tree Algorithm's Performance

Figure 4 provides a comparison of the performance of the proposed model with existing machine learning methods, specifically highlighting the metrics of precision, recall, and accuracy for the SVM algorithm. The methods compared include Decision Tree, SVM, KNN, and Modified Random Forest.

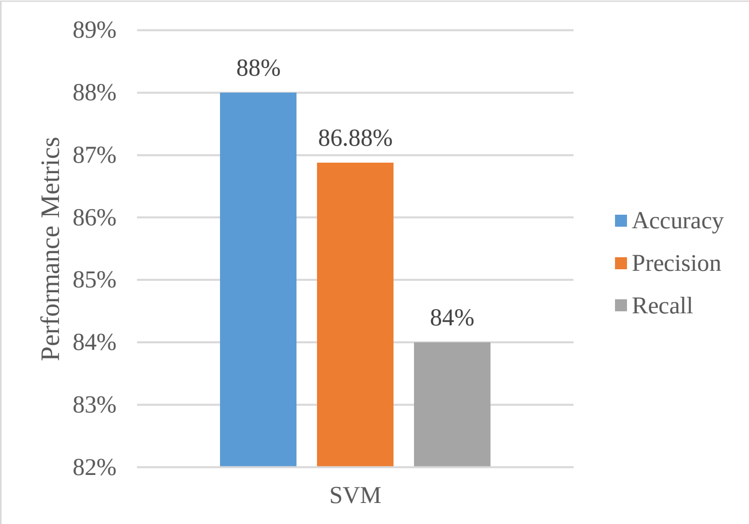

Figure 4. An assessment of the SVM algorithm's performance

The figure demonstrates that the proposed model outperforms the traditional SVM algorithm in terms of precision, recall, and accuracy, achieving values of 88%, 87.56%, and 80%, respectively. These results show an improvement over the standard SVM approach, indicating that the proposed method offers enhanced performance in classification tasks. By delivering higher precision and recall, the proposed model proves to be a more effective solution in comparison to the existing machine learning techniques evaluated in this study. Figure 5 provides a performance assessment of the KNN algorithm, comparing the proposed model with current machine learning methods such as Decision Tree, SVM, KNN, and Modified Random Forest. The figure focuses on key performance metrics, including accuracy, precision, and recall, as part of the evaluation.

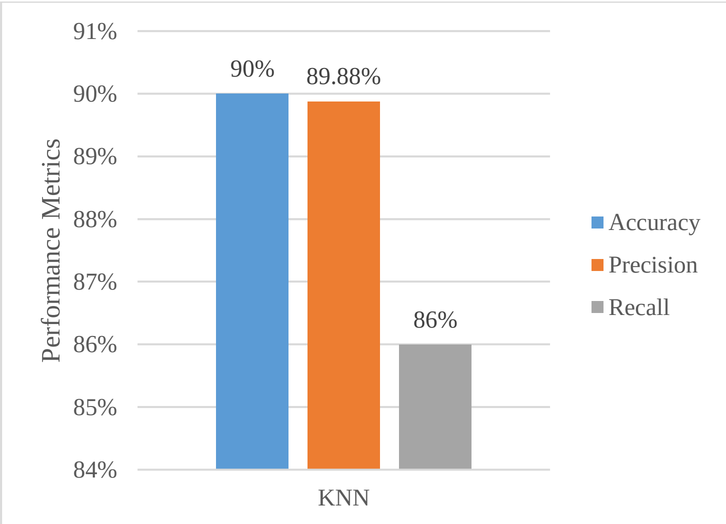

Figure 5. An assessment of KNN performance

The results from the figure show that the proposed model yields higher values for the KNN algorithm compared to existing methods. Specifically, the proposed system achieves 91% accuracy, 88.88% precision, and 82% recall, demonstrating a significant improvement over traditional KNN implementations. This indicates that the proposed approach is more effective in delivering accurate and reliable results, making it a superior alternative to the conventional KNN algorithm as well as other methods compared in this study. Figure 6 illustrates a performance assessment of the Modified Random Forest algorithm, comparing the proposed model with existing machine learning methods, including Decision Tree, SVM, KNN, and Modified Random Forest. The evaluation focuses on key metrics such as accuracy, precision, and recall.

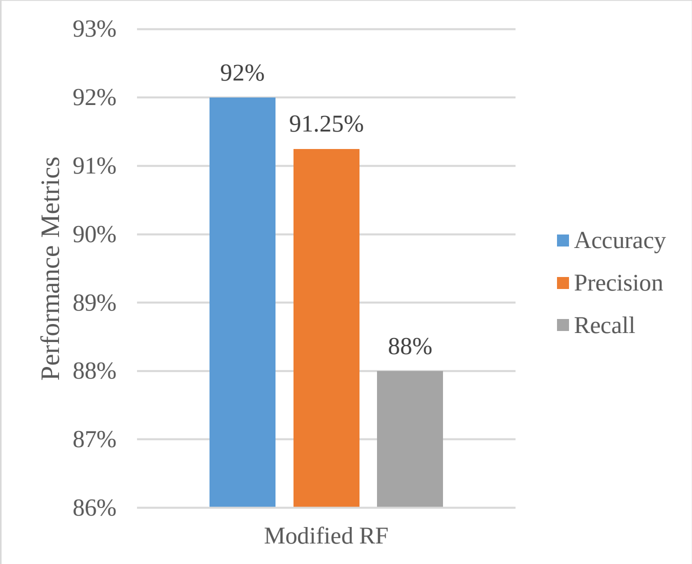

Figure 6. An assessment of Modified Random Forest's performance

According to the figure, the proposed system achieves superior performance with the Modified Random Forest algorithm, yielding the highest values compared to other methods. Specifically, it achieves 92% accuracy, 91.25% precision, and 88% recall. These results demonstrate that the proposed model significantly improves the performance of the Modified Random Forest algorithm, outperforming the other methods in terms of classification effectiveness. This suggests that the proposed approach offers a more accurate and reliable solution for the tasks evaluated, making it the most robust among the techniques considered. Figure 7 presents a time series performance evaluation, comparing the proposed model against existing machine learning methods, including Decision Tree, SVM, KNN, and Modified Random Forest. The evaluation focuses on precision, recall, and accuracy metrics, measured over time to assess how the models perform in dynamic or time-dependent scenarios.

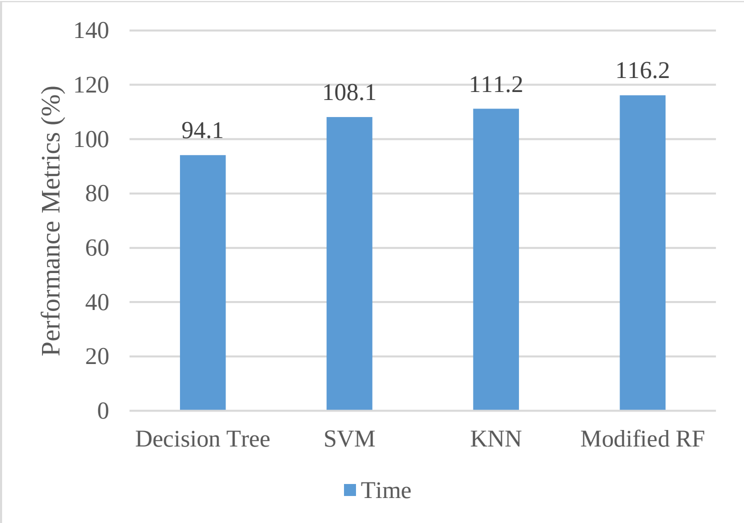

Figure 7. Time series performance evaluation

The figure reveals that the proposed model outperforms the current methods, achieving higher time series values of 108.4% for accuracy, 94.1% for precision, and 110.1% for recall. These results indicate that the proposed approach is not only effective in terms of accuracy and reliability but also demonstrates superior performance in time-dependent evaluations. The time series results suggest that the model maintains consistency and stability over time, making it a more efficient and reliable choice for time-sensitive machine learning tasks.

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7. Conclusion

This study has demonstrated the effectiveness of the proposed solution in addressing the complexity challenges inherent in the dataset while achieving superior accuracy, precision, and recall compared to existing machine learning algorithms. Specifically, the proposed model achieved an accuracy of 92%, precision of 91.25%, and recall of 88%, outperforming methods such as Decision Tree, SVM, and KNN. These results highlight the potential of integrating advanced approaches like deep learning and genetic algorithms, which, despite their significance in data analysis, have not yet received widespread attention in the machine learning community.

The key contribution of this work lies in providing a solution that not only improves accuracy but also enhances overall computational performance. By delivering higher precision and recall, the proposed approach addresses gaps in existing research and offers practical benefits for complex data analysis tasks. While the research meets its primary objectives, certain limitations remain, particularly concerning scalability and processing time for larger datasets. Future research should focus on optimizing the model to improve real-time performance and scalability across different datasets.

Moving forward, we plan to integrate the proposed model with a web server to improve accessibility and usability. Furthermore, future work will focus on refining the algorithms to exceed the current precision (91.25%) and recall (88%) while reducing processing time, ensuring the model's adaptability to more complex datasets and real-world applications. In conclusion, the model's ability to achieve 92% accuracy provides a solid foundation for future advancements in machine learning techniques, offering valuable insights into efficiently solving complex data analysis problems.

8. Declarations

8.1. Author Contributions

Conceptualization: S.G., M.I., S.S.M., and J.W.; Methodology: M.I. and S.S.M.; Software: S.G. and J.W.; Validation: S.G., M.I., S.S.M., and J.W.; Formal Analysis: S.G., M.I., S.S.M., and J.W.; Investigation: S.G. and J.W.; Resources: M.I. and S.S.M.; Data Curation: M.I. and S.S.M.; Writing Original Draft Preparation: S.G., M.I., S.S.M., and J.W.; Writing Review and Editing: M.I., S.S.M., S.G., and J.W.; Visualization: J.W.; All authors have read and agreed to the published version of the manuscript.

8.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

8.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

8.4. Institutional Review Board Statement

Not applicable.

8.5. Informed Consent Statement

Not applicable.

8.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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