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TrackNex: Real-Time Delivery Tracking and ETA Prediction

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Abstract: The rise of e-commerce and on-demand services makes real-time logistics visibility vital. Conventional tracking systems use milestone-based information and do not take into consideration the impact of dynamic variables like traffic and weather conditions, thus leading to faulty predictions about the time of delivery. This paper introduces TrackNex as an innovative approach to delivering real-time information on delivery using WebSocket communication and machine learning to provide accurate predictions of Estimated Time of Arrival (ETA). The model built using random forest regression provides an accuracy score of 0.99 on enriched data that takes into account traffic and weather conditions among others. The architecture of the system makes use of MongoDB for storage and Redis cache to enable high levels of concurrency.
Keywords: Real-Time Tracking, Estimated Time of Arrival (ETA) Prediction, WebSocket Communication, Role-Based Dashboards, Random Forest Regression, Predictive Logistics.

I. INTRODUCTION

The rise of e-commerce and on-demand logistics services has led to increased demand for more accurate and timely visibility in the supply chain process. The problem with the traditional logistics tracking system is that it is based on pre-defined milestones ("dispatched" or "out for delivery") that do not take into consideration variables such as traffic congestion, weather disturbances, and change of route, thus leading to poor predictions of ETA and operational inefficiencies.

New advances in ICT have made it possible to integrate digital capabilities into logistics operations, making processes much more efficient due to improved traceability and communication. Among these innovations are the use of machine learning for better prediction of ETA, as seen through the implementation of Random Forest Regression algorithm. Another example is the introduction of WebSocket for improved data transmission compared to the standard HTTP request-response paradigm. While there are existing solutions in the field, they are not able to seamlessly integrate real-time communication and prediction analytics into their systems. In order to fill this gap, this paper presents a solution named TrackNex which provides real-time delivery tracking through live delivery tracking based on WebSocket along with ETA prediction using machine learning models. This approach includes the use of scalable architecture with MongoDB as its database and Redis as its cache, as well as third-party APIs for traffic and weather conditions, making it more accurate. Role-based dashboard design also allows smooth interactions between customers, delivery drivers, and administration.

TrackNex is capable of fulfilling the requirements discussed above and can be used in today’s environment for deliveries.

II. LITERATURE REVIEW

The early studies on logistics tracking were mainly concentrated on making the process efficient by providing visibility through manual and IT-based methods. The problem was that these methods did not have any real-time functionality or predictive capability. With the advent of digital tracking devices, the researchers recognized the importance of information systems in facilitating traceability and coordination in logistics processes; however, these information systems were static and inflexible.

The development of ICTs led to the evolution of logistics systems, where cloud computing became an integral part for storing and processing vast amounts of data. These systems also used collaborative models, which facilitated coordination among different parties involved in logistics processes. Nevertheless, many of these systems ignored real-world issues, including traffic and weather conditions, which made the prediction of deliveries difficult.

Current advances in research have focused on the real-time and intelligent logistics management systems. IoT-based systems have allowed the monitoring of the process while cloud-based approaches have provided scalable data exchange opportunities. Machine learning algorithms have become popular for the prediction of ETA and route optimization purposes. Prediction models, using external information about traffic situation, weather changes, and other relevant data, have achieved much better prediction results than their traditional competitors.

At the same time, innovations in the field of communication systems can improve the speed of data exchange in real time. The use of WebSocket-based systems instead of regular HTTP requests can provide low latency and more efficient two-way data exchange. Microservices and cloud-native systems have been developed to allow high concurrency, modularity, and scalability. While modern technologies and their application allow creating a good infrastructure for logistics management, most solutions have certain limitations.

In particular, many systems do not include efficient integration of real-time communication with prediction modeling or they cannot leverage the usage of external data sources efficiently. Thus, the combination of these functions in one system is required to achieve better results.

III. OBJECTIVE OF THE PROJECT

1) Implementing an on-demand delivery tracker which will give real-time locations rather than milestone-based tracking. This will increase efficiency by increasing transparency and reducing any uncertainty in the process. The system will ensure customer satisfaction by giving live tracking for orders.
2) Using Random Forest Machine Learning algorithm for predicting ETA taking into account the various parameters such as traffic, weather, and other previous deliveries in order to provide more accurate predictions as opposed to conventional prediction models.
3) Using Node.js along with microservices, MongoDB and Redis as database solutions in order to create a scalable system architecture for ensuring high efficiency when handling the incoming requests.
4) Using Web Socket technology which is an excellent solution for transferring data in real-time without the need for HTTP requests.
5) Creating customized dashboards for customers, delivery partners and the administrators for ease of use of the system.

IV. RESEARCH DESIGN AND METHODOLOGY

A. *Modules and their Description*

1) User Modules

- User authentication and profile management
- Place orders and track orders
- Live tracking of deliveries(WebSocket Technology)
- ETA prediction with machine learning algorithms
- Check delivery history
- Notifications & alerts

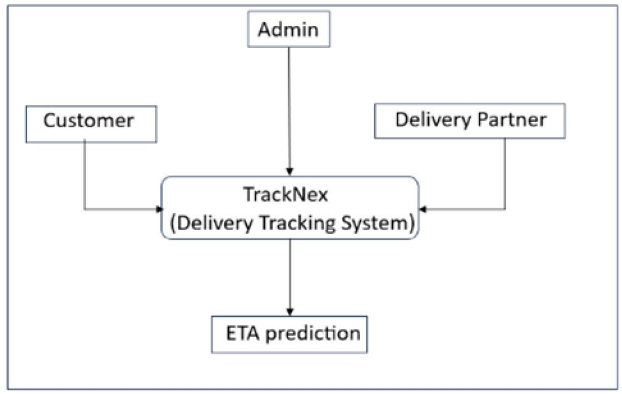
2) Admin Modules

- Fleet Management dashboard
- Assign and reassign orders
- Analyze performance and efficiency
- Data management of customers, partners, and orders
- API monitoring (traffic, weather)
- User & delivery partner management

3) Delivery Partner Modules

- Authentication and trip assignment
- Live location sharing
- Routing with traffic/weather information
- Update the status of delivery (picked, in-transit, delivered)
- Check delivery history and earnings

B. Data flow Diagram



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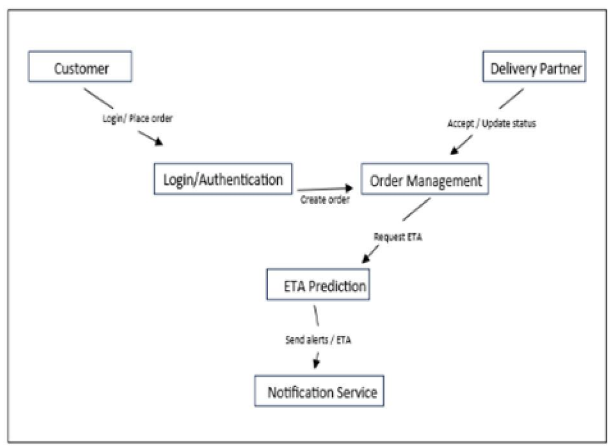

DFD level -2

V. PROPOSED SYSTEM

TrackNex, which is the system being proposed in this paper, is a smart and scalable real-time delivery tracking system aimed at solving the challenges faced by conventional logistics systems. Real-time communication, machine learning algorithms used to predict ETA, and a modular system architecture are some of the key aspects that contribute to the accuracy and continuous updating of delivery information.

This system takes advantage of WebSocket technology to ensure low latency and bidirectional communication between the client and server. This means users get live location data about their deliveries without delay. The system adopts a microservice architecture that involves the separate operations of several independent components such as frontend, backend, and machine learning models. The frontend utilizes Next.js while the backend uses Node.js and Express.js.

One of the most important components of the system is the ETA prediction mechanism, which is based on a Random Forest regression model. In order to obtain accurate results, the model works with a set of historical data that has been augmented with contextual information such as traffic condition, weather, distance, and timing. Such a solution allows for creating reliable and dynamic predictions that take into account changes in the real world.

Role-based features include customer ability to monitor order status, delivery partner ability to report location and status updates, and administrator control over fleet statistics. External APIs are used for receiving more information such as weather and traffic conditions. Overall, the suggested approach ensures scalability, efficiency, and high-quality user experience while being cost-efficient.

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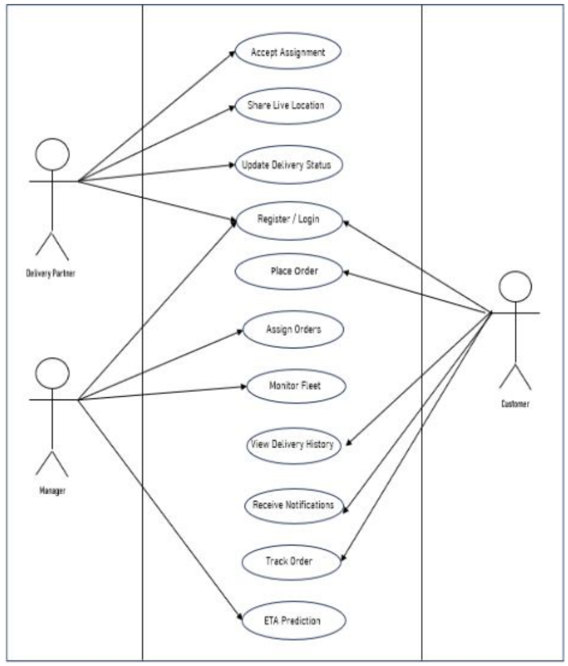
A. General Architecture



VI. DISCUSSION

A. Experimental Design

All experiments were executed on a machine running Ubuntu 22.04 LTS with an Intel Core i7-10th Gen CPU, 16 GB RAM, and no dedicated GPU. The whole stack was deployed with Docker Compose. The ML model training and testing were carried out with Python 3.10 using the following libraries: scikit-learn 1.3 and pandas 2.0. The latency and concurrency testing was done with Apache JMeter 5.6, simulating the number of clients concurrently sending requests ranging between 10 and 500.

B. ETAs Prediction Model Comparison

Evaluation of five regression models that were trained and tested using the same 80/20 train-test split of the same 18,500-record delivery dataset. All models were evaluated with three metrics: mean absolute error (in minutes), root-mean-squared error (in minutes), and R^2 score.

C. WebSocket Latency Testing

WebSocket cut down the average latency by 84.6% compared to HTTP polling with 10 users; even when 500 users were making requests, the latency difference was still substantial (69%). At 500 requests per second, WebSocket latency was under 300 ms, which ensured system response times within the required usability threshold. WebSocket latency increased linearly depending on the number of users (from 48 ms to 187 ms). It is easy to handle with Socket.IO routing and coordinate caching with Redis.

D. Feature Importance Analysis

To examine how the Random Forest model makes decisions, SHAP (SHapley Additive exPlanations) values were generated using 500 test cases. The top 5 features ranked based on descending order of mean absolute SHAP values were:

1) Distance left to travel: 35.2%
2) Traffic index: 24.7%
3) Weather index: 14.1%
4) Historical average delivery time: 11.3%
5) Partner average speed: 8.4%

Time of day contributed 4.8% while day of the week contributed only 1.5%. The results above reaffirm the fact that environmental features (traffic, weather) account for the second largest proportion of variation in ETA variance (38.8%).

VII. TECHNOLOGIES USED IN PROPOSED SYSTEM

The TrackNex software solution is designed according to a modern full-stack architecture. To render content effectively and provide responsive design solutions on the front end, frameworks such as Next.js and Tailwind CSS are used, while on the back end side Node.js and Express.js are employed in order to develop APIs and perform business logic. To ensure flexible storage of data, MongoDB is used, while Redis can be implemented for caching purposes. The arrival time predictor is built with the use of Python and scikit-learn libraries together with Flask in order to increase scalability of Random Forest modeling. Communication through WebSockets (Socket.IO) enables real-time interaction between various parties involved and ensures consistent data exchange. Other external APIs like Google Maps, weather and traffic data, are employed in order to increase the precision of predictions.

VIII. ADVANTAGES

TrackNex provides many benefits compared to regular logistics solutions by having live delivery tracking that continuously updates location data, thus enhancing the level of transparency and trust from customers. Machine learning-based ETA prediction based on traffic conditions, weather, and historical data further contributes to higher accuracy in prediction and improved planning. WebSocket is used for fast exchange of data and thus for increased system response time and enhanced customer experience. Microservices architecture provides an additional benefit related to the ability to manage a high number of users. Moreover, the choice of MongoDB and Redis facilitates more effective handling of data storage and retrieval, while role-based dashboards increase the convenience for different users.

IX. FUTURE SCOPE

The potential upgrades that can be considered to implement in TrackNex in the future might include improving the intelligence capability of the platform, making it scalable, and ensuring its reliability. The implementation of IoT sensors for collecting real-time information about the state of goods during transportation will make the application suitable for transportation where special logistics is needed for the delivery, including pharmaceuticals and food products.

What is more, blockchain technology may provide the opportunity to verify whether or not the goods are authentic. An expansion of functionality to cover other transportation modes like air or railway transport will allow the platform to become more versatile. Finally, a highly-developed chatbot interface based on AI can be implemented into the system.

X. CONCLUSION

This paper presented TrackNex, a fully featured, cloud-deployable, real-time delivery tracking platform that integrates WebSocket-powered live location updates, ETA predictions using Random Forests, and multi-stakeholder role-based dashboards into one scalable platform aimed at SME logistics companies. The system was thoroughly evaluated along three key performance indicators: the ML model's accuracy, the real-time communication latency, and system scalability in concurrent settings.

The suggested Random Forest regressor, enhanced by API data, demonstrated an impressive R^2 score of 0.9912 and an MAE of 1.84 minutes, outperforming Linear Regression, Decision Trees, SVR, and LSTM approaches while retaining a light enough footprint for deploying a microservice. The WebSocket (Socket.IO) real-time communication channel achieved an end-to-end latency of GPS updates within 48 ms under moderate load, yielding substantial improvements between 77% and 85% when compared against HTTP long-polling. The platform exhibited an average response latency of under 500 ms and an error margin of below 1% during 500 simultaneous users on a barebones cloud server setup, confirmed by the high (>91%) Redis cache hit ratio.

TrackNex is a much-needed solution in the field of logistics technology that offers a highly efficient and intelligent tracking platform without any compromises on real-time communication and prediction accuracy. Future plans in the upcoming stages will see integration of IoT sensors, deep reinforcement learning for route optimization, delivery proof using blockchain technology, and perhaps multi-modal logistics solutions as well.

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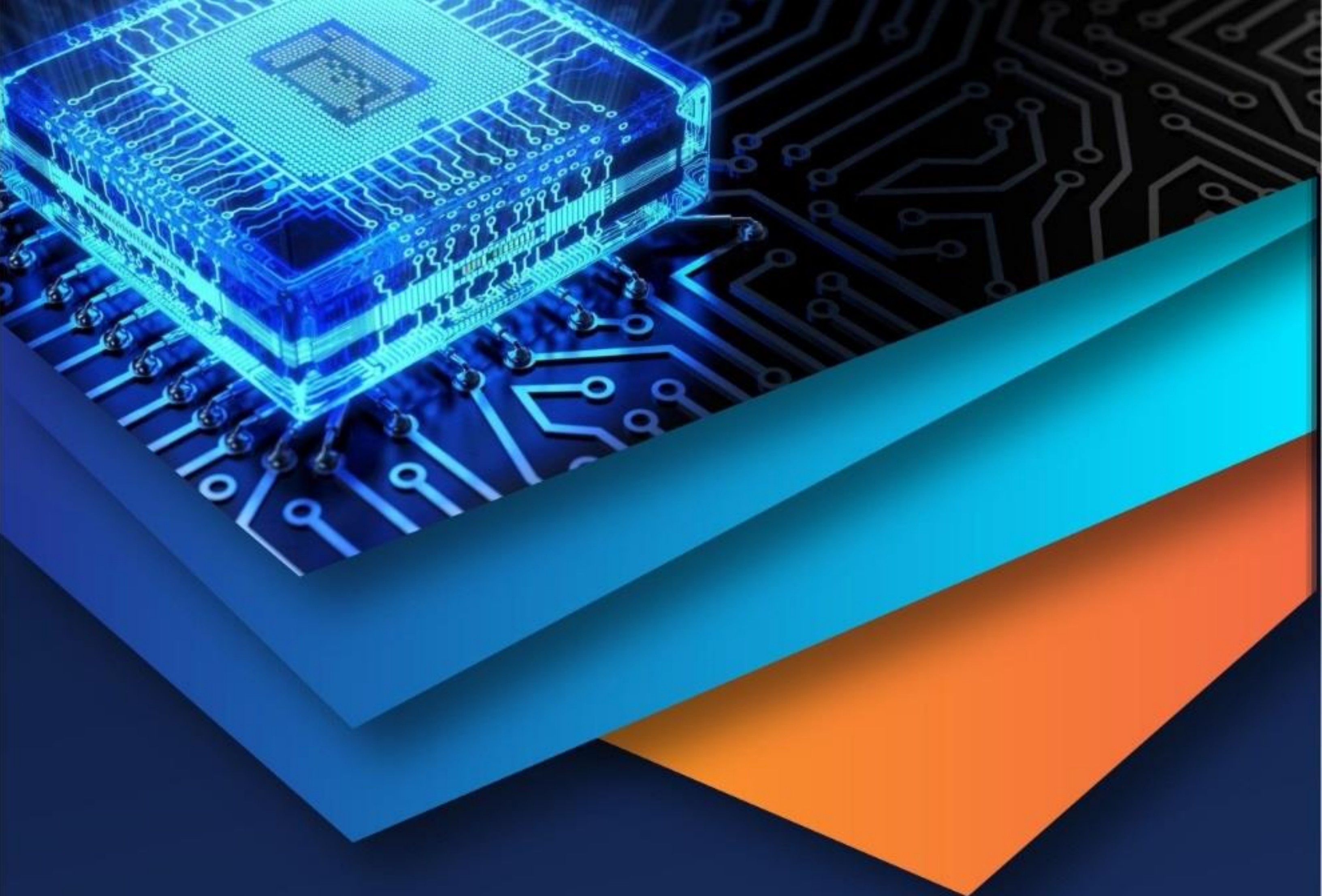

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