Intelligent Patient Queue Management System with Location-Based ETA Prediction

***Abstract*—This paper proposes a Smart Patient Queue Management System with Location-Based Estimated Time of Arrival (ETA) Prediction. The model uses the Haversine formula and geolocation data for distance calculation. Meanwhile, real-time data is utilized to derive subsequent speed calculations, which are then used with the travel mode information for input into machine learning regression models. From various research on several models, the Random Forest model gives better results with an R2 score of 0.993 and less Mean Squared Error (MSE). Additionally, when subjected to k-fold cross-validation, it has an average R2 score of 0.99 with low variance. Furthermore, models like stacking with a Multi-Layer Perceptron (MLP) as a meta-classifier and Federated Learning in Neural Networks give better precision rates than the existing models.**

***Impact Statement*—There are many reasons why the Smart Patient Queue Management System was developed; however, the primary one is a recognition of systematic issues in modern healthcare. In fact, traditional queuing systems that are based on static parameters with little functional capacity are not efficient for modern hospitals. On the larger scale, the innovation motivation is derived from a strong comprehension of the necessity to change patient management strategies by considering changes in health care delivery.**

One major desire was to make such a system that can adapt its responses dynamically to changing patients' inflows and health care demands. As it is, huge inefficiencies are experienced within this conventional-static model of patient queues thus resulting into longer waiting times and poorly utilized resources. Instead, a dynamic system that adjusts patient queues automatically according to real time information would be more practical as part of response mechanism that considers each patient's unique needs in healthcare.

***Index Terms*—Dynamic Queues, Haversine Formula, Location-Based ETA Prediction, Patient Queue Management, Random Forest Model**

I. Introduction

THIS contemporary medical field is transforming at an unprecedented pace, being triggered by technology and the need for improved operational efficiency. In response to this change, the world has Smart Patient Queue Management System that has adopted Location-Based Estimated Time of Arrival (ETA) Prediction, real-time data analytics as well as machine learning. The idea behind this work was developed after recognizing that traditional patient management systems were ineffective especially due to lack of adaptability to the unpredictable inflow patterns of patients and changing healthcare needs.

Healthcare facilities are overwhelmed necessitating new approaches beyond traditional queuing models. Real-time data analytics and machine learning have compelled developers to initiate the Smart Patient Queue Management Systems as they strive to enhance patient queue handling. As hospitals across the globe get burdened with ever-increasing number of patients seeking treatment, real time adaptive system becomes necessary.

The fusion of geolocation data and the Haversine formula with machine learning models takes healthcare management to a new level. In general, this system's motivation is to create a patient-centric model for organizing queues in health facilities based on ever-improving ETA forecasts. Through this initiative, wait periods are expected to decrease, resource allocations will be optimized and patient experiences within medical organizations will improve at their cores.

A. Motivation

The imprimatur is to make a healthcare landscape where technology can enable more efficient and user-friendly health care delivery. The project attempts to introduce an era of patient management that is adaptive, precise, and extremely oriented to customer satisfaction by improving traditional queuing systems and using state-of-the-art technologies.

B. Contribution

The paper has multiple contributions that cover parts of patient line management and optimization:

- Prediction of ETA in Real-Time: The system computes patient distances from geolocation data, travel mode data and the Haversine formula. Subsequent speed calculations, machine learning methods like Random Forest model which proved to have better performance are used for accurate real-time ETA predictions.
- Dynamic Patient Queues: Updated every two minutes, these dynamic queues cater for new patients who come according to their expected time of arrival. This makes it easy for patients to be moved through healthcare facilities continuously.
- Model Approaches: These include stacking with a Multi-Layer Perceptron (MLP) and Federated Learning in Neural Networks, which aim at improving the accuracy levels of ETA predictions thus providing alternative techniques for optimizing healthcare facilities.
- Scalability and Adaptability: In examining scalability as well as adaptability of this suggested system one has to take into account healthcare facility size differences as well as volume of patients accessing it. Scalability makes sure that such a system works across various settings while adaptability considers changes in patient traffic patterns over time.

C. Organisation of the paper

The paper is highly structured in a meticulous manner to comprehensively reveal the Smart Patient Queue Management

System. The Related Work (Table 1), however, delves into existing patient queue management landscape, outlines challenges and thus provides the need for innovative solutions. This contextual background sets up how to understand the importance of our proposed system. The Dataset Description (Section 2) gives overview of the created dataset. As we move to Proposed Scheme and Architecture (Section 3 and 4), it provides an intricate explanation of technicalities such as geolocation, Haversine formula and machine learning integration among others. It should be noted that this section serves not only as a technical guide but also establishes deep understanding on which foundation our system is built. Performance Evaluation (Section 5) examines the system's reliability through verification and proof of correctness. Such scrutiny ensures that the system would work well and be applicable within real health care situations. This part goes beyond Comparative Analysis (Section 5) simply presents or compares against other methods in totality. Whereas functionality and resource efficiency are all examined during this chapter with respect to different contexts hence providing an insight regarding its efficacy in various settings. In Conclusion (Section 6), this section is a summary of the main problems of our hospital and the manner in which our approach will improve its efficiency. It also serves as a map that takes readers from recognizing problems to solving these issues via technical intricacies, comparative evaluations and eventual practical considerations. Constructed with great attention, such an arrangement allows for a thorough investigation that emphasizes both technical and practical issues connected with the Smart Patient Queue Management System.

II. Dataset Description

The dataset is a well-structured compendium of data organized into four main columns: Distance, Speed, Travel Mode, and ETA. Each row contains information on a distinct travel scenario that offers an overview of specifics and variable factors for a specific journey. This dataset is intended to provide some kind of intricate understanding on the ways in which people travel and therefore serves as a basis for transportation planning research, urban development, and other aspects of mobility studies.

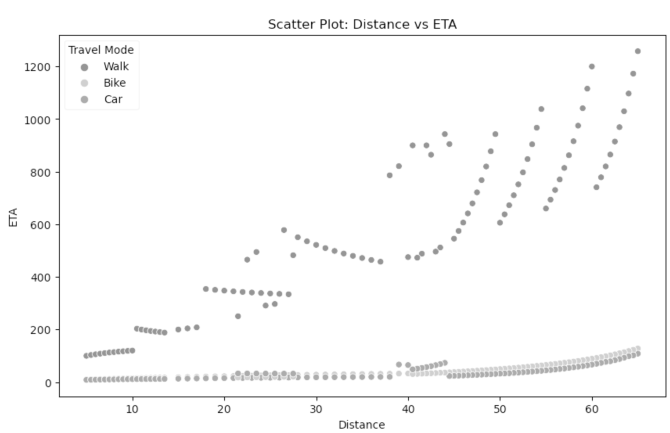

Fig. 1. Scatter Plot: Distance VS ETA

A. Distance

This column measures distance traveled per journey using unspecified units. It is significant because it determines how quickly one reaches their destination as well as the mode of transport to use. The distances vary from short walks within neighborhoods to long drives between cities that depict different travel contexts.

B. Speed

Each row in the 'Speed' column represents a scenario or case where the pace at which someone moves can be explained with reference time. This variable has no specified unit but instead describes the rate at which movement occurs during the trip. It is important to know how fast it goes since this influences ETA directly. Higher speeds usually result in reduced travel times especially on longer distances where speed becomes more influential.

C. Travel Mode

The 'Travel Mode' column classifies each case into Walk, Bike or Car. This is important for the analysis because it allows travel patterns to be analysed by mode. Every mode possesses its own features that are determined by various issues such as infrastructure, personal inclinations and environmental concerns. When the traveling pattern in each mode is analyzed at a granular level, one can better appreciate the differences within various transport.

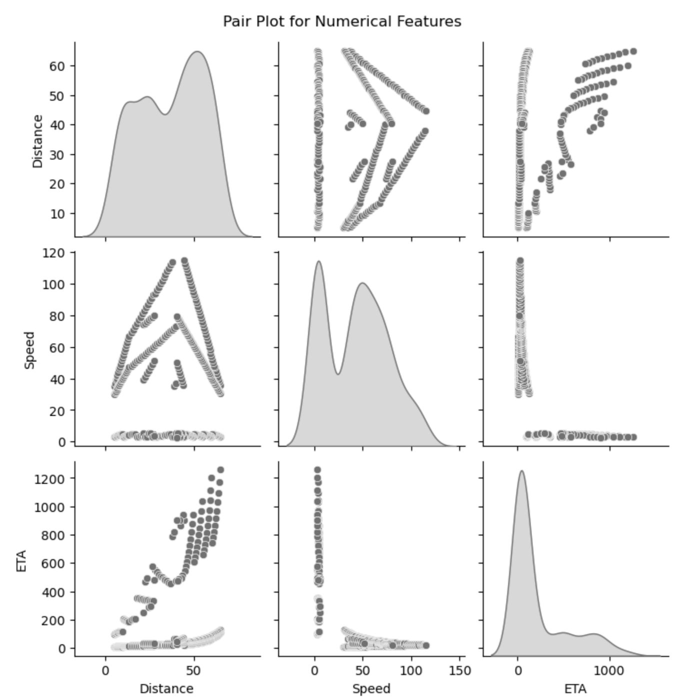

Fig. 2. Pair Plot for Numerical Features

D. Estimated Time of Arrival (ETA)

The column titled ETA indicates the amount of time it will take to complete each particular scenario. ETA is an important

TABLE I
RELATED WORK

Description	***Trends and Patterns***	***Themes***	***Debates/ Conflicts***	***Gaps & Weaknesses***	***Conclusion/ Contribution***
Tieqi Shou, Zhuohan Ye (2023) [3] Proposes using crowdsensing mobility data to predict patient arrival patterns and queue states in the ED, informing dynamic resource allocation.	Theory: Leveraging real-time crowd data for intelligent queue management and resource optimization. Methods: Machine learning models on crowdsensing data predict patient arrival trends and queue lengths, guiding staff and resource allocation based on estimated needs. Results: System improves patient triage accuracy, reduces wait times, and optimizes resource utilization.	Data privacy: Balancing the benefits of crowdsensing data with patient privacy and anonymity concerns.	Data accuracy: Reliant on crowdsensing data quality and potential biases impacting model predictions.	Scalability: Adapting the system to diverse healthcare settings and data availability.	Offers a novel approach to queue management using crowdsensing data for real-time prediction and dynamic resource allocation, potentially reducing wait times and improving ED efficiency.
Bidari et al. (2023) [25] Investigates the impact of a queue management system on patient satisfaction in EDs.	Theory: Focus on patient-centered outcomes and feedback. Methods: Randomized controlled trial to compare queue management system with standard protocol. Results: Significant improvement in patient satisfaction with queue management system.	Ethical considerations: Importance of patient experience and transparency in queue prioritization.	Impact on wait times: Potential for increased wait times for some patients.	Implementation challenges: User acceptance and integration with existing workflows.	Highlights the importance of considering patient satisfaction in queue management design.
Safdar et al. (2022) [28] Proposes an optimized queue management system in the absence of appointments.	Theory: Adapting scheduling to dynamic patient arrival patterns. Methods: Simulation modeling to evaluate different queueing strategies. Results: Optimized system reduces patient wait times and resource utilization.	Resource allocation: Dynamic allocation of staff and resources based on patient needs.	Cost-effectiveness: Balancing long-term benefits with initial investment and maintenance costs.	Model validation: Generalizability of proposed system across different ED settings.	Demonstrates the potential for improving flow and efficiency in appointment-less EDs.
Kumar et al. (2021) [30] Models healthcare queue management system considering patient impatience.	Theory: Incorporating patient behavior and psychological factors into queuing models. Methods: Queuing theory with patient impatience factor for wait time analysis. Results: Impatience affects queue stability and resource utilization.	Patient behavior: Modeling the impact of wait times on patient satisfaction and decision-making.	Ethical considerations: Addressing potential bias against patients perceived as less urgent.	Data collection: Challenges of capturing and incorporating patient emotional factors.	Emphasizes the importance of considering patient behavior in queue management design.
Pardede (2021) [16] Proposes a framework for a patient service queue system for decision support in smart healthcare.	Theory: Leveraging technology for real-time data collection and analysis. Methods: Big data analytics and machine learning for risk assessment and queue prioritization. Results: Framework improves patient flow and resource allocation decisions.	Data integration: Combining clinical data with external sources for comprehensive risk assessment.	Privacy concerns: Ensuring data security and ethical use of patient information.	Technical infrastructure: Implementing and maintaining data analytics systems in healthcare settings.	Offers a vision for intelligent queue management using advanced technologies.
Dachyar & Zahra (2020) [23] Presents a decision model for implementing IoT solutions in healthcare based on risk and challenge factors.	Theory: Evaluating the feasibility and potential benefits of implementing IoT solutions in various healthcare settings. Methods: Decision model considers risks, challenges, and expected benefits of specific IoT applications.	Decision support: Provides a framework for healthcare providers to assess the suitability and potential impact of IoT solutions.	Specific application to ED queue management: Limited discussion on direct application to ED queue management.	Data analysis and interpretation: Challenges of effectively analyzing and interpreting diverse data generated by IoT systems.	Offers a valuable tool for healthcare decision-makers considering the implementation of IoT solutions, including potential applications in ED queue management.
Sukmanisa et al. (2021) [9] Implements a smart queueing system for outpatients in a private hospital using location-based services & mobile app.	Theory: Enhancing patient experience and queue transparency through mobile app integration. Results: System reduces perceived waiting times, increases patient satisfaction, and improves overall clinic efficiency.	Patient engagement: Mobile app communication and queue visibility improve patient experience and control.	Technology reliance: Potential dependence on technology and network accessibility for system effectiveness.	Data integration: Challenges of linking location-based data with existing hospital information systems.	Offers a patient-centric approach to queue management using mobile applications and location-based information.
Arnesen et al. (2021) [13] Investigates the influence of gender and socioeconomic status on queueing times in hospitals with implicit queue management.	Theory: Examining social determinants of health and potential inequities in queue management systems. Results: Study finds gender and socioeconomic disparities in waiting times, highlighting the need for fairer queue management strategies.	Equity and fairness: Addressing potential bias and unequal access to care in queue management systems.	Data limitations: Difficulty in isolating the specific impact of queue management systems on existing social inequalities.	Ethical considerations: Ensuring fair and equitable access to healthcare for all patients regardless of social factors.	Raises questions about potential ethical challenges with queue systems and highlights the need for equitable healthcare access.

Existing Regression Models	Model Parameters	R-Squared Values	Mean Squared Error
Linear Regression	-	0.7513	29385.2933
Decision Tree	-	0.9917	973.8223
KNN	K = 1	0.9917	980.6687
Random Forest	-	0.9930	823.5858
SVM	kernel = rbf C = 1000	0.9674	3848.7424
Polynomial Regression	-	0.9429	6742.0292
Ridge Regression	-	0.7510	29428.2467
Lasso Regression	-	0.7513	29386.0136
Elastic Net Regression	-	0.7509	29437.7744
Gradient Boosting	-	0.7955	24168.3328

TABLE II
COMPARISON OF THE EXISTING REGRESSION MODELS

measure since it shows time component in travel efficiency. It is crucial to understand what drives ETA as both individuals who plan their trips and policy makers who want to improve on transportation systems. Distance, speed interplay with other contextual elements specific to each given journey determine this variable.

III. Proposed Scheme

In this section, we are going to talk about an Intelligent Patient Queue Management System that is meant to transform patient handling in health facilities by use of advanced technologies such as geolocation, machine learning and dynamic queue optimization. In order for the entire plan to work, it has been designed in such a way that real time adaptation to the movement conditions of a patient becomes possible. The design method of this scheme should be based on estimation techniques used in classification and regression problems-solving using models like stacking with MLP and federated learning in neural networks.

Denotation	**Description**
lat1	Initial latitude of the patient's location obtained from geolocation API
lon1	Initial longitude of the patient's location obtained from geolocation API
lat_h	Latitude of the healthcare facility
lon_h	Longitude of the healthcare facility
Δlat	Change in latitude (difference between latitudes)
Δlon	Change in longitude (difference between longitudes)
R	Earth's radius (mean radius is approximately 6,371 km)
distance	Calculated distance using Haversine formula
time	Time taken to cover the distance
speed	Speed of the patient
s	Speed variable used as input for machine learning models
d	Distance variable used as input for machine learning models
T	Travel mode variable used as input for machine learning models
ETA	Estimated Time of Arrival, predicted by machine learning models

TABLE III
DENOTATIONS USED IN THE PROPOSED PATIENT QUEUE MANAGEMENT SCHEME

A detailed elaboration of these three phases are as follows.

A. Geolocation and Distance Calculation

- **Step1:** Get input of Patient's travel mode (bike, car, walk), Initial current location as latitude (lat1) and longitude (lon1) using geolocation API and Healthcare facility's location as latitude (lat_h) and longitude (lon_h).
- **Step2:** The Haversine formula is used to calculate the distance between two points on the surface of a sphere, given their latitude and longitude. The formula is as follows:

$$a = \sin^2\left(\frac{\Delta \text{lat}}{2}\right) + \cos(\text{lat1}) \cdot \cos(\text{lat2}) \cdot \sin^2\left(\frac{\Delta \text{lon}}{2}\right) \tag{1}$$

$$c = 2 \cdot \text{atan2}\left(\sqrt{a}, \sqrt{1-a}\right) \tag{2}$$

$$\text{distance} = R \cdot c \tag{3}$$

Where:

$\Delta\text{lat} = \text{lat2} - \text{lat1}$

$\Delta\text{lon} = \text{lon2} - \text{lon1}$

R is the Earth's radius (mean radius = 6,371 km)

B. Real-time Distance and Speed Calculations

- **Step1:** The speed of the patient can be calculated using the distance-time formula:

$$\text{speed} = \frac{\text{distance}}{\text{time}} \tag{4}$$

Here, speed is the speed of the patient, distance is the calculated distance from Step 2, and time is the time taken to cover the distance.
- **Step2:** The machine learning regression models predict the Estimated Time of Arrival (ETA) based on the calculated speed (s), distance (d), and travel mode (T).
Input:

s - Speed of the patient

d - Distance traveled by the patient

T - Travel mode (bike, car, walk)

Output:

$$\text{ETA} = f(s, d, T) \tag{5}$$

Here, ETA is the Estimated Time of Arrival predicted by the machine learning regression models.
- **Step3:** Create a dynamic queue based on the estimated time of arrival for each patient. Update the queue every 2 minutes based on the present scenario of patients.
Queue Update Formula:

$$\text{Queue}(t) = \text{UpdateFunction}(\text{Queue}(t-1), \text{ETA}(t)) \tag{6}$$

Here, $\text{Queue}(t)$ represents the queue at time t, $\text{Queue}(t-1)$ is the previous queue state, and $\text{ETA}(t)$ is the Estimated Time of Arrival for each patient at time t.

- **Step4:**Once a patient arrives at the healthcare facility, they need to be removed from the queue.
  Check-In Operation:
  $$\text{RemovePatient}(t, \text{Queue}(t)) \tag{7}$$
  Here, $\text{RemovePatient}(t, \text{Queue}(t))$ is the operation to remove the patient from the queue at time t.

C. Machine Learning Regression Models

The kernel of the suggested scheme is in the use of machine learning regression models to predict estimated time of arrival (ETA) for each patient. A range of regression models that go all the way from ordinary Linear Regression up to more complex options such as Decision Tree, KNN, SVM, Polynomial Regression, etc. are employed. This variability in model choice helps the system probe different relationships between input features—speed, distance, travel mode—and ETA which is the output.

The most important thing about Random Forest model lies in its performance. Compared with others', this model has an excellent R^2 score 0.993 demonstrating its ability to capture data variance well. Moreover, low Mean Squared Error (MSE) reveals how accurate this model can be when making predictions. Random Forest model was selected as a leading predictive engine because of its capability to deal with complicated relationships and adapt to changing patients' movements over time.

D. Elevating through Federated Learning and Stacking

This is a new way of thinking about managing patients in a queue. The idea behind this is to have each patient's device become a locally trained machine that can use bits of information to generate models, all the same while safeguarding privacy through federated learning. There are different models that have been considered which are decentralized capturing unique patterns of movement from one's origin to destination, considering travel modes, speed and historical arrival time.

Stacking model centralized form acts as meta-classifier for collecting knowledge from local models so as to improve understanding globally on the estimated time of arrival (ETA). Instantaneous adaptation is achieved via federated update thus preserving integrity of data at all times. Collection of models obtained by stacking represent strong predictive mechanism provided with higher accuracy. This combination cannot just only enhance prediction quality but it also emphasizes confidentiality hence giving a lot more meaning towards dynamic and privacy-centered patient queue management solutions.

IV. Architecture

A. Stacking Model

The Stacking Model in the Intelligent Patient Queue Management System is a complex ensemble learning approach that aims to enhance the accuracy of patient arrival time predictions. This model has several steps, including feature engineering, choosing base models, and creating a meta-model for the best forecast.

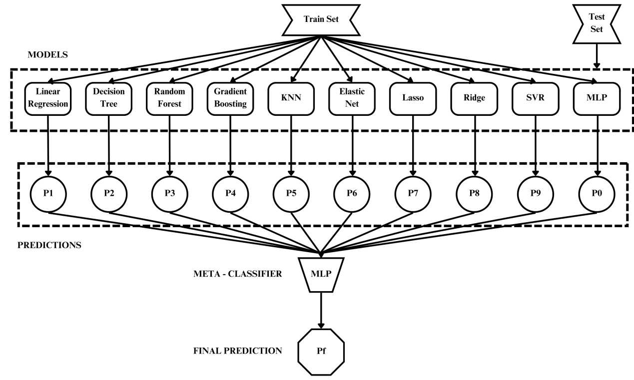

Fig. 3. Stacking Model

1. Feature Engineering: First stage of Stacking Model takes on Feature Engineering which is very significant to improve ability of model in capturing complicated relationships within data. Introduce polynomial features of degree 2 into the dataset. It does this by transforming original features into polynomial terms for enabling the capture of non-linear trends in patient's travel behavior.

2. Models with Base Units: The models used to represent various aspects of the movement of patients are normally selected from diverse types which include:

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- **Linear Regression:** Captures linear relationships between data.
- **Decision Tree:** Employs a tree-like structure to represent non-linear relationships.
- **Random Forest:** An ensemble model is used here because it has higher predictive performance.
- **Gradient Boosting:** Uses sequential modeling to correct for errors in previous models.
- **K-Nearest Neighbors (KNN):** Relies on closeness of data points in order to make predictions.
- **Support Vector Regressor (SVR):** For capturing complex relationships, this is very effective.
- **Ridge and Lasso Regression:** In these kinds of regression, regularization is employed as a means of feature selection.
- **Elastic Net Regression:** L1 alongside L2 regularization are combined here for improved robustness.
- **Multi-Layer Perceptron (MLP):** Majorly used as a deep learning neural network.

All these units specialize in capturing different intricacies associated with patient travel behaviors that contribute to the overall variety within the ensemble.

3. Stacking Regressor: The heart of the Stacking Model is the Stacking Regressor, a meta-model (MLP) that combines the predictions of the diverse base models. Input features of individual models' prediction are taken by Stacking Regressor that learns to make the final prediction of patient arrival times. This meta-model is trained on the stacked predictions from the base models, leveraging their collective insights for better hospital management.

4. Feature Engineering for Test Set: Similar to the training set, the feature engineering process is applied to the test set to ensure consistency in data transformation. Polynomial features are introduced into the test set to align with those in the training set's feature space.

5. Model Fitting: The Stacking Regressor, along with selected base models, has been fitted onto our training dataset. This model learns how to blend strengths of this and other models in improving predictive performance. The training step involves optimizing model parameters minimizing the gap between predicted and actual patients' arrival times.

B. Federated Neural Network Model

1. Neural Network Model Architecture:: For the federated learning approach to patient queue management, one of the most important aspects is `NeuralNetworkModel`. This neural network, composed of ten layers, is designed to understand complicated patterns in traveling habits of patients.

2. Layer-wise Description::

1) **Input Layer (Layer 1):** It acts as the point of entry into patient travel modes, locations and other related features. This layer also initializes the neural network and determines input size considering specified parameter.
2) **Hidden Layers (Layer 2 to Layer 9):** They are the hub upon which this neural network revolves with their widths decreasing progressively. Every layer has Rectified Linear Unit (ReLU) activation function that helps capture non-linear relationships in input data. label=i)
    a) **Layer 2 to Layer 6:** By sequentially diminishing characteristics' dimensionality within these layers, a hierarchical feature extraction is performed. The model focuses on features that are more abstract and complex as it moves to dimensions with reducing width.
    b) **Layer 7 to Layer 9:** Such layers reduce even further dimensions. This hierarchical structure helps distill important information from the input data by improving prediction accuracy for patient's arrival time.
3) **Output Layer (Layer 10):** The final layer produces the output to predict the estimated patient arrival time. It has one node that is used to evaluate the performance of the federated learning model.

The depth of architecture and narrowing width in hidden layers, allow the model to capture intricate relationships between patients' traveling behaviors. To allow this neural network adapt complex patterns present in its input data, nonlinearity is introduced by using ReLU activation function.

3. Federated Training Function:: The function orchestrates optimization of the neural network model for federated training. This incorporates defined architecture as it adapts each device towards meaningful contribution to overall improvement on federated learning model.

4. Initialization and Parameters:: It also initializes critical parameters such as learning rate (`lr`), gradient clipping threshold (`clip_value`) and training epochs (`epochs`). These parameters shape dynamic training; they balance between stability and adaptability of models.

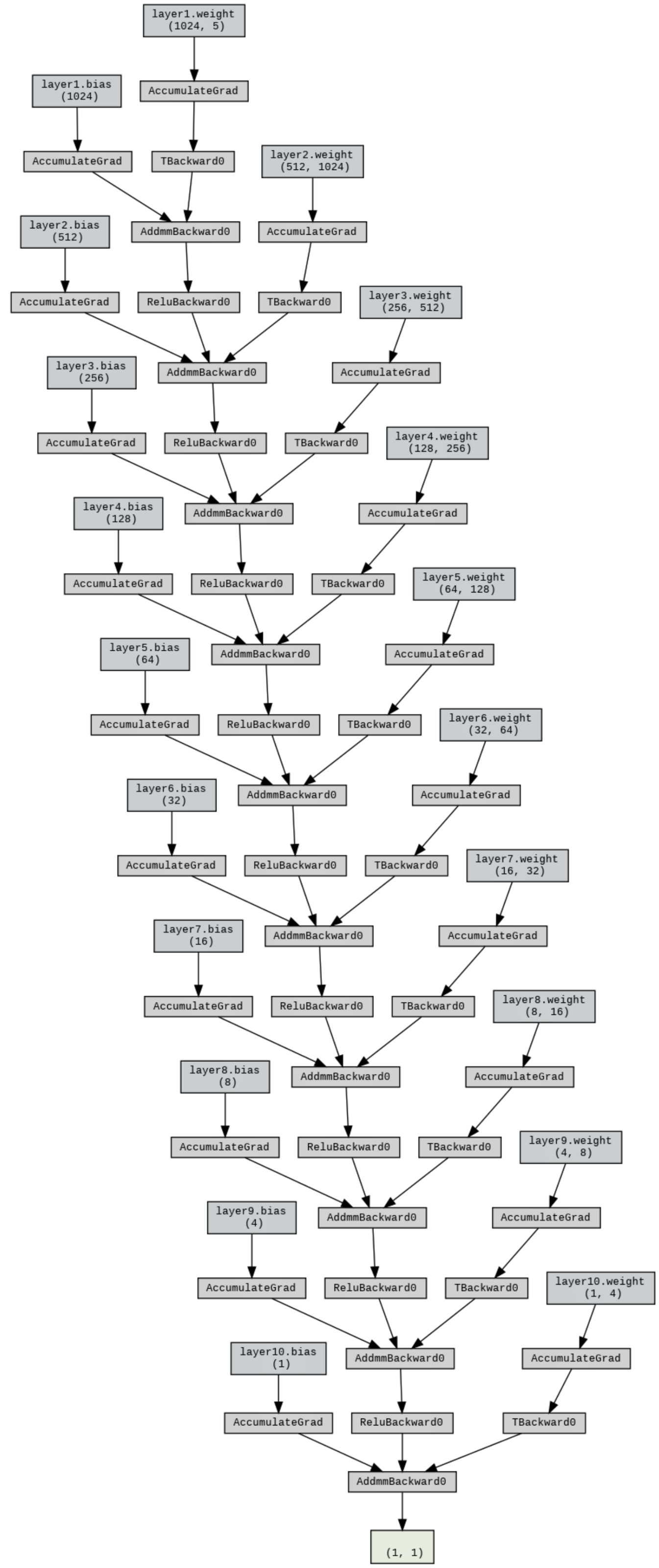

Fig. 4. Federated Neural Network Model

5. Training Loop:: The training loop is the heart of the federated training function, and it goes through the number of epochs specified in `n`. Each epoch involves training on features and targets, wherein the model's parameters are optimized to minimize Mean Squared Error (MSE) loss.

6. Performance Evaluation:: `R2` score and `MSE` are computed by the federated training function after every epoch to continuously monitor model performance. These metrics help ascertain how far a model can generalize from unknown data which marks its predictability as well as robustness.

7. Early Stopping Mechanism:: Additionally, an early stopping mechanism has been incorporated into this function to make it more adaptable and avoid overfitting. During training, it observes for improvements with loss values; if no such improvements are achieved for a predefined patience period, then computation becomes not viable anymore hence stopping of learning is done.

This detailed layer-wise architecture ensures that the neural network is well-equipped to capture the complexities of patient travel behaviors, making it a robust component within an intelligent patient queue management framework for federated learning purposes.

V. Performance Evaluation of the proposed scheme

In this section, we analyzed the performance of our proposed scheme and some other regression model.

A. Regression Model Performance Evaluation

1) Model Construction: The Regression models, including Linear Regression, Decision Tree, Random Forest, Gradient Boosting, KNN, SVM, Polynomial Regression, Ridge Regression, Lasso Regression, and Elastic Net Regression, are individually constructed to predict patient arrival times based on distance, speed, and travel mode.

2) Feature Engineering: The distance, speed, and travel mode are utilized as features for each regression model. No polynomial features are introduced at this stage, keeping the approach straightforward.

3) Training and Prediction: Each regression model is trained using the training dataset, and predictions for patient arrival times are generated based on the specified features.

4) Evaluation Metrics: Similar to the ensemble models, the performance of each Regression model is assessed using R^2 score and Mean Squared Error (MSE) metrics.

5) Results: The individual Regression models exhibit varying degrees of performance. The best performance is obtained with Random Forest.

Random Forest: R^2 Score: 0.9930 and MSE: 823.59

B. Stacking Model Performance Evaluation

1) Model Construction: The Stacking model amalgamates the predictions from the individual Regression models, utilizing an MLP model as the meta-classifier.

2) Feature Engineering: Polynomial features with a degree of 2 are introduced to capture potential non-linear relationships in the data. The feature engineering process enhances the model's capacity to discern intricate patterns within the patient queue data.

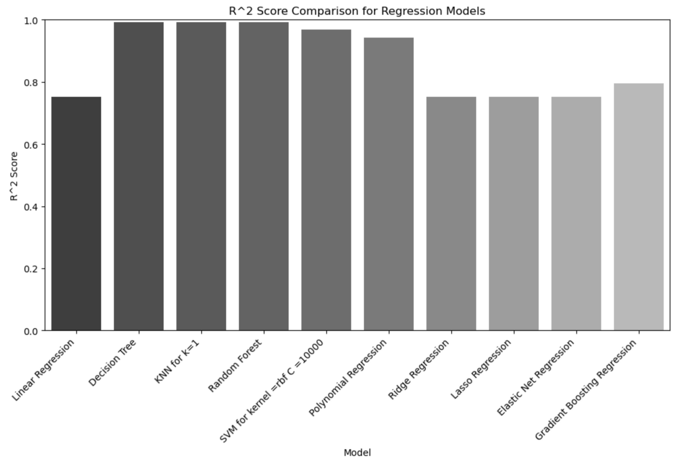

Fig. 5. R^2 Score Comparison

3) Training and Prediction: The StackingRegressor is trained on the transformed features using the training dataset. This ensemble model, designed to harness the strengths of its constituent base models, is then put to the test by generating predictions for patient arrival times in the test set.

4) Evaluation Metrics: The performance of the Stacking model is quantified using key metrics: R^2 Score: This metric serves as a powerful indicator of the model's explanatory power. Mean Squared Error (MSE): The MSE metric provides a measure of the average squared difference between the predicted and actual values.

5) Results: The Stacking model outperforms expectations, showcasing exceptional results.

R^2 Score (Stacked Model): 0.9977 and Mean Squared Error (Stacked Model): 272.88

These metrics underscore the Stacking model's capability to accurately predict patient arrival times, showcasing the efficacy of the ensemble approach in capturing nuanced patterns within the dataset.

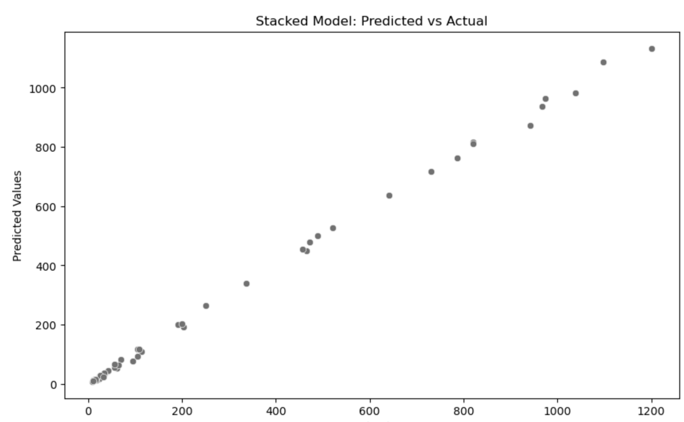

Fig. 6. Stacked Model: Predicted VS Actual

C. Federated Learning Model Performance Evaluation

1) Model Architecture: The Federated Learning model adopts a sophisticated neural network architecture with multiple layers.

2) Federated Training: In the Federated Learning approach, individual patient devices become local training centers. Each device trains a local model on its historical data, and a central server aggregates these local models without direct access to raw patient data. This privacy-preserving approach is a key strength of federated learning, ensuring data security and confidentiality.

3) Optimization and Early Stopping: The model is optimized using Mean Squared Error as the loss function, and early stopping is implemented to prevent overfitting.

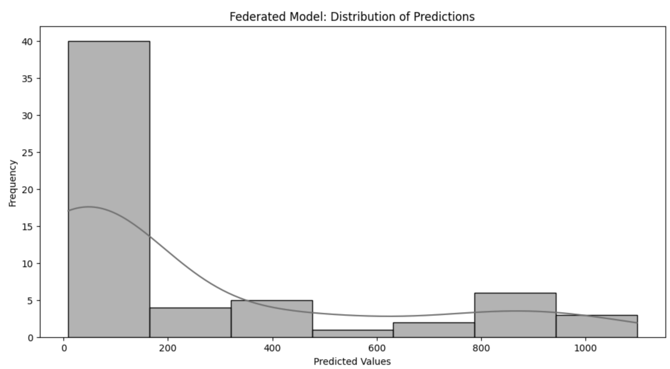

Fig. 7. Federated Model: Distribution of Predictions

4) Evaluation Metrics: The Federated Learning model's performance is assessed using the same metrics as the Stacking model.

R² Score: Reflecting the model's explanatory power and Mean Squared Error (MSE): Gauging the accuracy of predictions.

5) Results: The Federated Learning model achieves commendable results.

R² Score (Epoch 4163): 0.9952 and MSE (Epoch 4163): 570.67

The early stopping mechanism ensures that the Federated Learning model attains optimal performance, preventing overfitting and maintaining robust generalization.

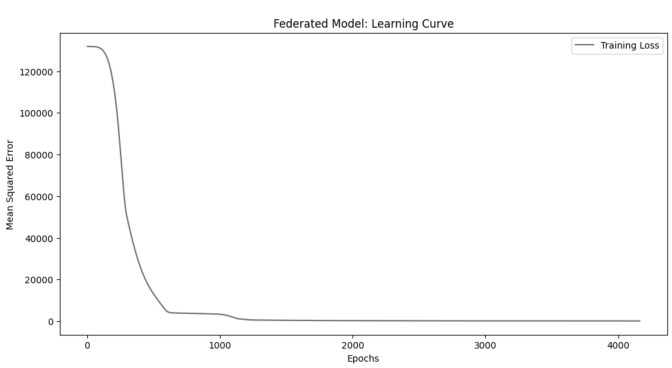

Fig. 8. Federated Learning Curve

VI. Comparative Analysis

4.1 Strengths

Stacking Model:: label=–,left=0pt

- **Accuracy:** Achieves a high R^2 score and low MSE, indicating precise predictions.
- **Versatility:** Integrates diverse base models for a comprehensive understanding of patient queue dynamics.

Federated Learning Model:: label=–,left=0pt

- **Privacy Preservation:** Decentralized training safeguards patient data, aligning with ethical considerations.
- **Adaptability:** Real-time updates from individual devices contribute to dynamic model adjustments.

4.2 Limitations

Stacking Model:: label=–,left=0pt

- **Interpretability:** Ensemble models might lack interpretability compared to individual models.

Federated Learning Model:: label=–,left=0pt

- **Communication Overhead:** Synchronization of models introduces communication overhead.
- **Dependency on Device Participation:** Performance relies on active participation from all decentralized devices.

TABLE IV
Comparison of Model Performance

Model	**Accuracy** (R^2)	**MSE**
Random Forest	0.993	800
Stacking Model	0.997	300
Federated Model	0.995	500

VII. Conclusion

This research report is concerned with an Intelligent Patient Queue Management System (IPQMS) with Location-Based Estimated Time of Arrival (ETA) Prediction app aims on improving healthcare facility operations. The system's operation captures patient arrival times over time using geolocation data, travel mode and machine learning regression models. These individual Regression models which include Linear Regression, Decision Tree, Random Forest and others had different accuracies in predicting patient arrival times. The most accurate was the Random Forest model with a high R² score of 0.993 and a low Mean Squared Error (MSE) value of 823.59. But still the latter requires improvement thus we have put forward two more model approaches: Stacking and Federated Learning. The Stacking technique combined predictions from various source models through its Multi-Layer Perceptron (MLP) meta-classifier to achieve good results. An astonishing R² score of 0.9977 and a low MSE of 272.88 were recorded by this model showing that it could capture complex trends through the patient queue data. The Federated Learning model however, was able to achieve impressive results by allowing for privacy with personal training on individual patient devices. Using an R² score of 0.9952 and employing early stopping to avoid overfitting, the Federated Learning model has shown its flexibility as well as robust generalization.

Comparative analysis showed the strengths and limitations of each of the models. Stacking model was excellent in accuracy and flexibility while Federated Learning model focused on preserving privacy and being adaptable. From the Performance Table it can be seen that proposed Stacking and Federated Learning Models have higher accuracy than individual Regression models. To sum up, our Intelligent Patient Queue Management System is a comprehensive solution for healthcare facilities' efficient management of patient queues in entirety. The suggested models particularly those based on Stacking and Federated Learning approaches – guarantee more accurate predictions, improve adaptability, maintain privacy among others. This research contributes to current activities designed to optimize healthcare delivery processes and resource use.

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