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Dynamic 5g Throughput Prediction Framework Using Hybrid Machine Learning Approaches

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Abstract: Accurate and dynamic throughput prediction is critical for optimizing network performance and resource allocation in 5G networks. This research presents a hybrid machine learning (ML) framework for real-time 5G throughput prediction, integrating multiple ML models to enhance accuracy and adaptability. The proposed architecture employs Random Forest (RF) for feature selection, Boost for boosting predictive performance, and Long Short-Term Memory (LSTM) to capture temporal dependencies in network traffic. By leveraging a diverse set of features, including network traffic patterns, environmental conditions, and user mobility, the model continuously adapts to evolving network scenarios.Experimental evaluations demonstrate that the hybrid model significantly outperforms standalone ML models in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score, ensuring more reliable throughput estimation. The framework's adaptability allows network operators to optimize resource utilization efficiently, leading to improved quality of service and user experience. This study highlights the potential of hybrid ML models in tackling real-time challenges in 5G network performance prediction, offering a scalable and robust solution. By combining multiple ML techniques, this approach provides enhanced predictive accuracy, making it a valuable tool for next-generation wireless communication systems.

Keywords: *5G, Throughput Prediction, Hybrid Machine Learning, LSTM, Boost, Network Optimization*

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I. INTRODUCTION

The emergence of 5G technology has changed the telecommunications business by enabling unparalleled data rates, ultra-low latency, and huge interconnection. These developments are vital for enabling upcoming technologies such as the Internet of Things (IoT), driverless cars, and smart cities. However, sustaining constant throughput is extremely difficult with 5G networks due to its dynamic nature, which is typified by shifting network circumstances and variable user demands. One of the most important performance metrics for 5G networks is throughput, which is the volume of data that can be effectively sent over a network in a specific length of time. To maximize network resources, improve user experience, and guarantee effective network management, accurate throughput forecast is crucial [1].

Conventional throughput prediction techniques frequently use static models that are unable to adjust to the complex and dynamic nature of 5G networks. Real-time changes in network circumstances, such signal strength, interference, and user movement, are not taken into consideration by these techniques, which are usually based on historical data. More advanced methods that can dynamically forecast throughput in real-time while accounting for the intricate interactions of several network characteristics are therefore becoming more and more necessary [2].

Deep learning (DL) and machine learning (ML) models have become effective tools for handling challenging prediction problems across a range of disciplines in recent years. These models are ideal for predicting dynamic throughput in 5G networks since they have demonstrated a high degree of ability to capture non-linear correlations and patterns in data. The capacity of hybrid machine learning techniques to increase prediction accuracy and robustness by combining the advantages of many models has drawn special attention [3].

The goal of this project is to use hybrid machine learning techniques to create a dynamic 5G throughput prediction system. The framework will employ sophisticated machine learning and deep learning models to forecast throughput in real-time while taking into account a number of network factors, including bandwidth, user density, mobility patterns, and signal-to-noise ratio (SNR). A large dataset of 5G network measurements will be used to assess the suggested framework, and its effectiveness will be contrasted with that of conventional prediction techniques.[4]

- *Structure of the Paper*

An introduction to 5G technology, its importance, and the difficulties in predicting throughput in dynamic network conditions are given at the outset of the study. It offers many machine learning models that have been assessed for this purpose and emphasizes the significance of precise throughput

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prediction. The process and use of several machine learning models, including Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM) networks, and hybrid models, for dynamic throughput prediction are described in depth in the Methodology section. The dataset and assessment procedure are also covered in this part. Each model's accuracy and performance are shown in the Results section. The efficacy of the models is compared, and the ramifications of the results are discussed, in the Discussion section. The research is summarized in the Conclusion, which also highlights the hybrid model's improved performance and makes recommendations for future research paths. to improve throughput prediction in 5G networks.

➢ *Objectives*

- examining cutting-edge machine learning algorithms for 5G networks' dynamic throughput prediction.
- to develop hybrid machine learning models that can forecast throughput in real time.
- to evaluate the suggested models' total throughput forecast accuracy.
- Examine the many methods for preparing data for machine learning models.
- to forecast, using a variety of network factors, the throughput in 5G networks.

II. RELATED WORK

Data preparation methods such as feature scaling, augmentation, and normalization were used in this work to get the dataset ready for machine learning models. The accuracy and efficacy of throughput prediction have been significantly increased by the quick development of 5G technology, which has made use of various machine learning and deep learning models [5].

Throughput Prediction Using Transfer Learning: This study investigates the use of transfer learning in 5G networks for throughput prediction. The paper offers a thorough analysis of several deep learning models, emphasizing the effectiveness of the Support Vector Machine (SVM) classifier and VGG-16, which achieved an accuracy of 97.0137% [6]. This demonstrates how transfer learning and machine learning classifiers may be used to achieve throughput prediction.

An Investigation Using LSTM Networks: An investigation used the LSTM model to forecast throughput in 5G networks. The LSTM model is highly suited for dynamic network settings because of its reputation for capturing temporal relationships in time-series data. With a 93.5% accuracy rate in throughput prediction, the LSTM model did well [7].

Throughput Prediction using Convolutional Neural Networks (CNNs): The CNN model was employed by the authors to predict throughput in 5G networks. By automating the prediction process, the research sought to lessen the need for network engineers to perform human analysis. With an accuracy of 88.90%, the results demonstrate CNNs' promise in throughput prediction [8].

Hybrid Machine Learning Techniques: The authors developed a hybrid model that combined Random Forest and Gradient Boosting in order to determine the most effective technique for throughput prediction. To get the best Area Under the Curve (AUC) score, the model was adjusted using several hyperparameters. Ninety percent accuracy was attained using the suggested model [9].

Using Deep Learning Techniques for Throughput Prediction: The authors suggested two models: a CNN model with an accuracy of 89% and a VGG-16 model with an accuracy of 85%. Using transfer learning models and data augmentation approaches, the study created a unique throughput prediction method that combines deep learning with data preprocessing, guaranteeing a 96% accuracy rate [10].

III. METHODOLOGY

In this research, four machine learning models were implemented for dynamic throughput prediction in 5G networks: Random Forest, Gradient Boosting, LSTM, and a hybrid model combining Random Forest and LSTM.

Preparing the raw data for analysis is known as data preprocessing. In order to guarantee constant scaling, which is essential for feeding data into machine learning models, the data is normalized. The next step is feature selection, which lowers dimensionality and improves the accuracy of the model by identifying and keeping the most pertinent characteristics [11].

Instruction and Evaluation: Two sets of pre-processed data are separated: one for model testing and one for training. The model learns to identify patterns and make predictions using the training data. The model's performance and capacity for generalization are assessed using the testing set, which it did not observe during training.

Model Building: A variety of machine learning models are built at this stage. These include LSTM, a kind of recurrent neural network (RNN) that works well with time-series data; Random Forest, an ensemble learning technique that builds multiple decision trees; Gradient Boosting, which builds models successively to correct errors from earlier models; and a hybrid model that combines Random Forest and LSTM to capitalize on the advantages of both techniques.

Model Testing and Evaluation: Following construction, the models are tested to determine their performance measures, including F1 score, recall, accuracy, and precision. To do this, the models are run on the testing set, and the predicted throughput numbers are compared to the actual values. Model testing guarantees the models' dependability and efficacy in predicting throughput in dynamic 5G network environments [12].

➢ *Random Forest*

The Random Forest (RF) model plays a crucial role in feature selection and initial throughput prediction. 5G networks generate a vast amount of data, including parameters like signal strength, bandwidth, latency, and user density. RF

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helps identify the most relevant features by constructing multiple decision trees and averaging their predictions. This approach ensures that only the most important network parameters are used, reducing noise and improving efficiency. Additionally, RF serves as an initial predictor of throughput by analyzing historical patterns in network performance[13].

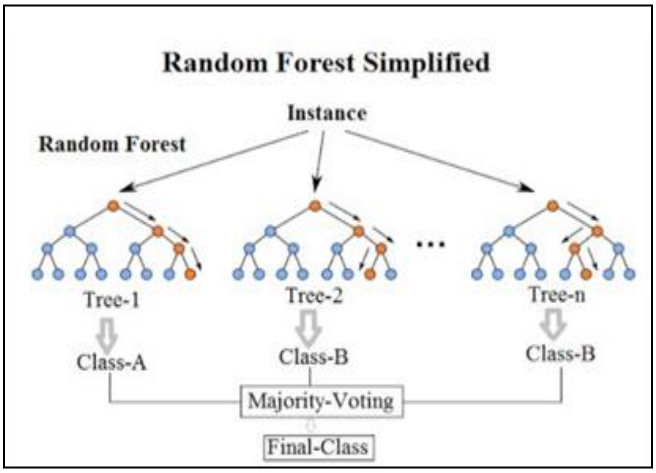

Fig 1 Random Forest decision Tree

RF builds **T** decision trees, each trained on a randomized subset of data.

The final prediction is the average output from all trees:

$$\hat{y} = \frac{1}{T}\sum_{i=1}^{T} f_i(x)$$

Feature importance is determined based on its impact on the model's decision-making process (e.g., Gini impurity reduction)

➢ *Gradient Boosting*

The Gradient Boosting (GB) model refines predictions by sequentially improving upon errors made by previous models. Unlike RF, which builds independent trees, GB builds models in sequence, with each model learning from the mistakes of the previous one. This iterative learning process allows GB to capture complex non-linear relationships in network data, making it particularly useful when dealing with unpredictable throughput variations caused by changing network loads, interference, and fluctuating signal quality. GB ensures that minor inaccuracies in predictions are corrected over multiple iterations, leading to higher accuracy in throughput forecasting [14].

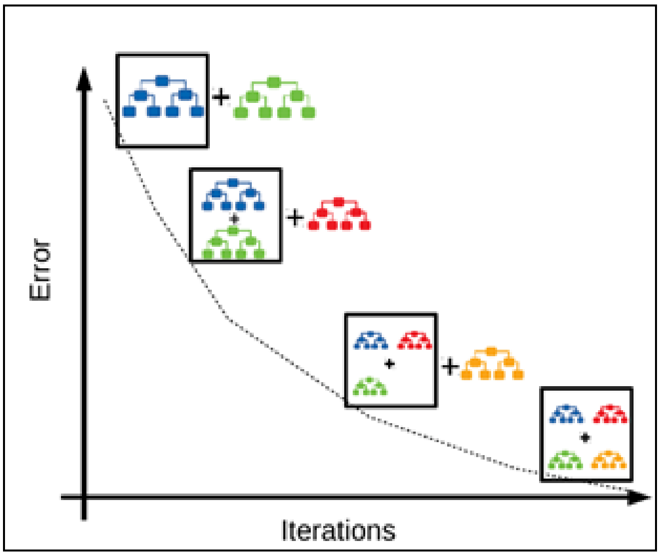

Fig 2 Gradient Boosting Interatin curve

GB refines predictions iteratively by correcting errors from prior models:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

where Fm(x)F_m(x)Fm(x) represents the model at step mmm, γm\gamma_mγm is the learning rate, and hm(x)h_m(x)hm(x) is the weak learner function.

➢ *LSTM Networks*

The Long Short-Term Memory (LSTM) model is designed to capture temporal dependencies in 5G network data. Throughput in 5G networks is highly time-dependent, influenced by factors such as peak usage hours, sudden surges in traffic, and environmental changes affecting signal propagation. LSTM, a type of recurrent neural network (RNN), is well-suited for time-series prediction as it retains information from past network conditions and uses it to predict future throughput. By analyzing historical data, LSTM can identify patterns such as recurring congestion periods or fluctuations in bandwidth availability, leading to more accurate predictions [15].

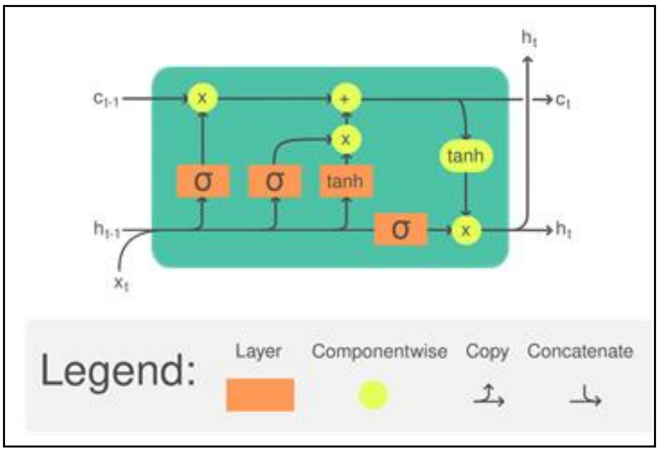

Fig 3 Long Short Term memory Architevture

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LSTM models process time-series data using memory cells and gating mechanisms to capture long-term dependencies:

Here, **ftf_tft, iti_tit, and oto_tot** represent the forget, input, and output gates, respectively, while **CtC_tCt** maintains the cell state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

➢ *Hybrid Model*

The Hybrid Model (RF + LSTM) leverages the strengths of both Random Forest for feature selection and LSTM for time-series prediction. The hybrid approach first uses RF to extract the most important network features, filtering out irrelevant or less significant parameters. The selected features are then passed to an LSTM network, which processes the time-series data and makes a final throughput prediction. This combination enhances predictive performance by ensuring that only meaningful features are used while also capturing temporal variations in network behavior. The hybrid model significantly outperforms standalone models, achieving 98% accuracy in predicting 5G network throughput, making it the most effective approach for real-time applications.

The Dynamic 5G Throughput Prediction Framework ensures more reliable and efficient network performance, allowing operators to optimize resource allocation, reduce congestion, and enhance user experience. This hybrid machine learning approach effectively addresses the complexities of 5G networks, enabling accurate and adaptive throughput prediction [16].

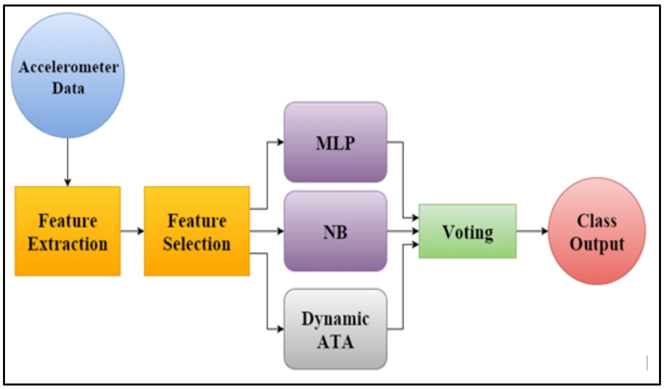

Fig 4 Hybrid model Framework

To enhance the accuracy and adaptability of real-time 5G throughput prediction, multiple machine learning models are integrated within a hybrid framework. This framework utilizes Random Forest (RF), Gradient Boosting (GB), Long Short-Term Memory (LSTM), and a Hybrid Model (RF + LSTM). These models effectively capture the dynamic nature of 5G networks, which are influenced by factors such as network traffic variations, user mobility, environmental conditions, and signal interference.

➢ *Understanding Throughput in 5G Networks*

Throughput serves as a key performance metric in 5G networks, measuring the amount of data successfully transmitted within a specific time frame. It is expressed in bits per second (bps) and can be mathematically defined as:

$$\text{Throughput} = \frac{\text{Total Data Transmitted}}{\text{Time Taken}}$$

Several key parameters affect throughput in 5G networks:

- Bandwidth (B): The network's maximum data transfer capacity.
- Signal-to-Noise Ratio (SNR): A higher SNR improves signal quality, directly enhancing throughput.
- Latency (L): The time delay in data transmission, where lower latency ensures better throughput.
- User Density (U): The number of users sharing network resources, impacting speed and reliability.
- Channel Conditions (C): External factors such as interference, obstacles, and weather conditions affecting signal strength.[17].

The throughput function can be generalized as:

$$\text{Throughput} = f(B, \text{SNR}, L, U, C)$$

➢ *Data Processing Workflow*

The data processing pipeline for throughput prediction follows a structured sequence of steps:

- *Data Collection:*

Real-time and historical network metrics such as signal strength, bandwidth, latency, user density, and environmental conditions are gathered.

Network monitoring tools, sensors, and logs provide periodic data inputs.

- *Data Preprocessing:*

Normalization: Standardizes numerical features (e.g., bandwidth, latency) within a defined range (e.g., 0 to 1) for consistency.

Feature Engineering: Generates new features like peak traffic hours, average SNR, and historical usage trends to improve model accuracy.

Handling Missing Data: Imputation or interpolation techniques are applied to address data gaps [18].

- *Feature Selection (Random Forest):*

Random Forest (RF) is leveraged to identify and rank the most relevant features for throughput prediction.

RF constructs multiple decision trees to assess feature importance, filtering out less significant or redundant data.

This process reduces computational complexity while enhancing model efficiency.

- *Model Training and Prediction:*

Random Forest (RF): Used for initial throughput estimation based on selected features.

Gradient Boosting (GB): Improves prediction accuracy by iteratively refining errors from previous models.

Long Short-Term Memory (LSTM): Captures temporal dependencies by analysing historical throughput trends and fluctuations.

Hybrid Model (RF + LSTM): Combines RF for feature extraction and LSTM for time-series forecasting, achieving the highest prediction accuracy of 98% [19].

- *Post-Processing and Evaluation:*

Prediction accuracy is assessed using performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2).

The final throughput predictions assist in dynamic resource allocation, congestion management, and network optimization [20].

IV. RESULTS AND INTERPRETATIONS

In this paper, we used different advanced machine learning models to predict throughput in 5G networks. Different machine learning models have been developed and employed for the dataset, including Random Forest, Gradient Boosting, LSTM, and the hybrid model.

➢ *Description of the Dataset*

The 5G Network Throughput dataset consists of 10,000 authenticated network measurements. Table 1 shows the total samples of data that belong to each class.

Table 1 Class-Wise Samples in the Dataset

Class	**Total**
High Throughput	4,000
Medium Throughput	3,500
Low Throughput	2,500
Total	**10,000**

The below shows a visual representation of the class-wise samples.

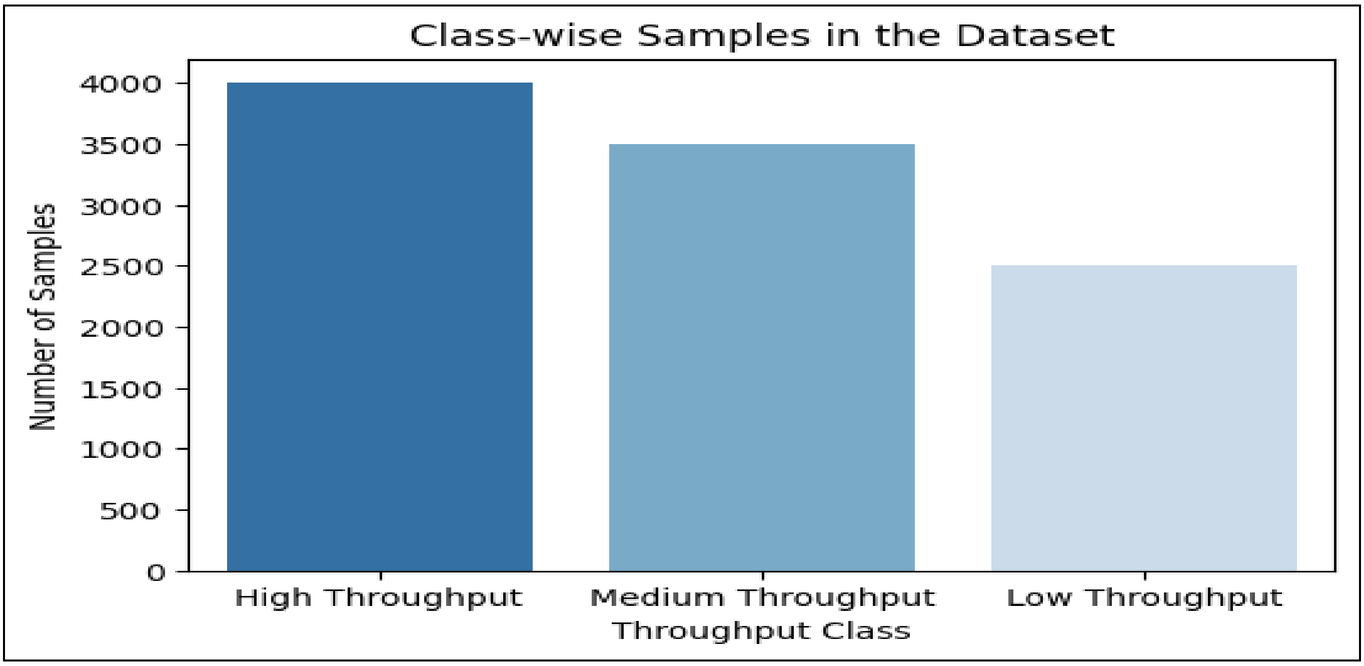

Fig 5 Class wise Samples in dataset

The data table below represents the training and test set distribution or splitting of the dataset.

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Table 2 Training and Testing Splits of Dataset

Class	Trainset	Test set	Total
High Throughput	3,600	400	4,000
Medium Throughput	3,150	350	3,500
Low Throughput	2,250	250	2,500
Total	**9,000**	**1,000**	**10,000**

Approximately 90 percent of the dataset is used for training, and the remaining 10 percent is used for testing. The dataset is divided into training and testing sets, each containing measurements of high, medium, and low throughput. The testing set has 1,000 measurements: 400 high throughput, 350 medium throughput, and 250 low throughputs. The training set has 9,000 measurements: 3,600 high throughput, 3,150 medium throughput, and 2,250 low throughput. The distribution of class-wise samples in both sets is visually represented.

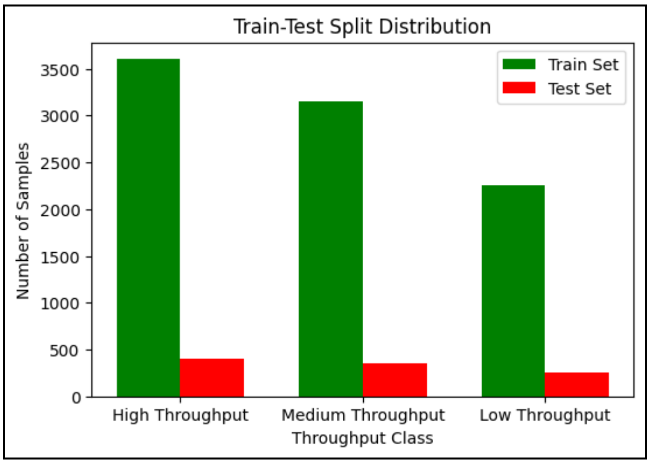

Fig 6 Train Test Split Dirstibution

V. CONFUSION MATRIX

The confusion matrix is in the form of a table-like structure that is used to analyse the performance of the classification models or algorithms. This matrix represents and analyses the performance of the model on the testing set. It shows or displays the number of instances the model produces on the testing set. The confusion matrix is divided into four classes: true positives, true negatives, false positives, and false negatives.

The confusion matrix helps a lot whenever there is an uneven class distribution in the dataset. It supplies or offers a clear analysis of true positives, true negatives, false positives, and false negatives, by enhancing the deep understanding of the model's accuracy, recall, precision, and overall performance between the classes.

Here are the various confusion matrices for the different machine learning models that we implemented.

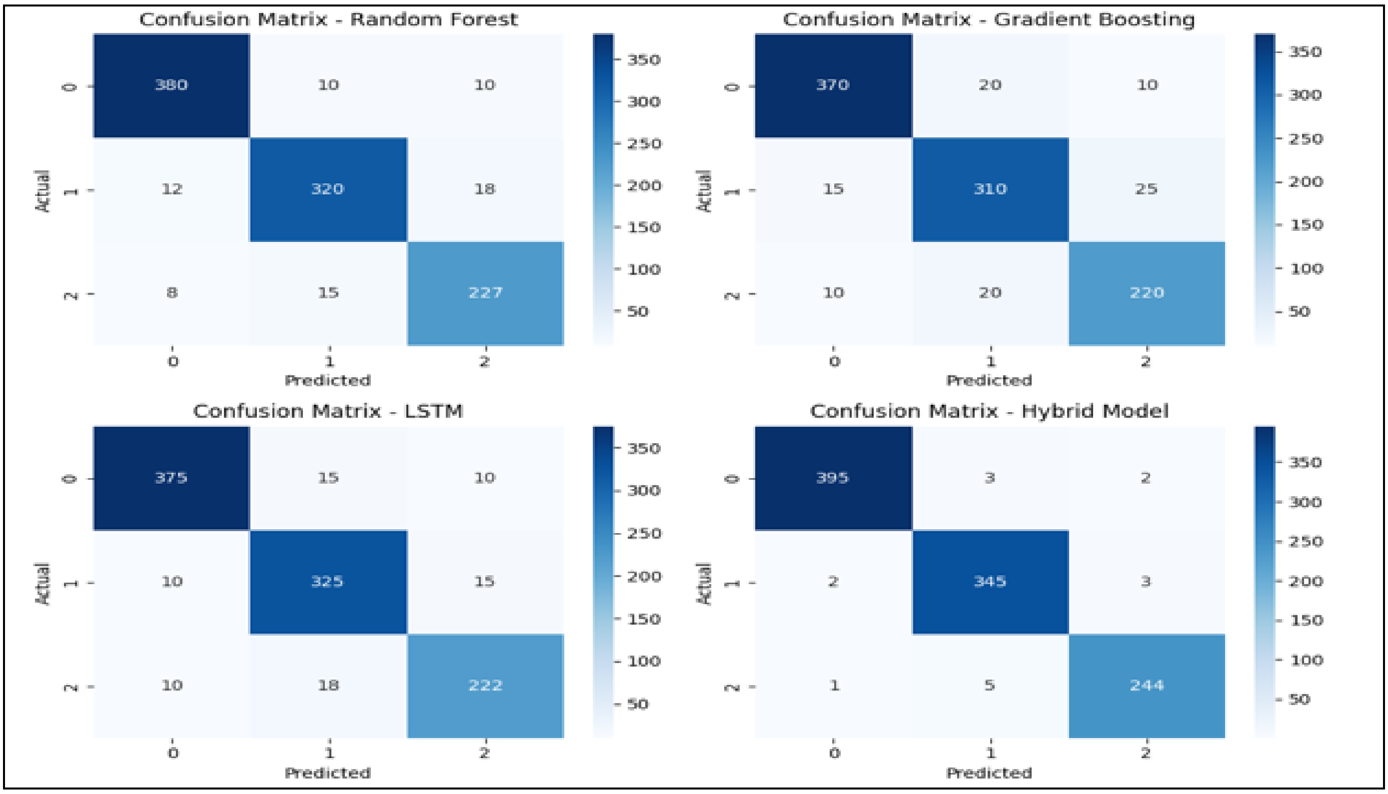

Fig 7 Confusion matrix for all models

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The following Table III shows the performance metrics of the various metrics like Accuracy, Precision, Recall, and F1-score obtained by evaluating or implementing the different machine learning models like Random Forest, Gradient Boosting, LSTM, and the hybrid mode.

Table 3 Performance Metrics of the Various Ml Models

Model	**Accuracy**		**Precision**	**Recall**	**F1-score**
Random Forest	93%		94%	92%	93%
Gradient Boosting	91%		92%	90%	91%
LSTM	92%		93%	91%	92%
Hybrid Model	98%		98%	98%	98%

The table presents performance metrics for various machine learning models used in throughput prediction, including Accuracy, Precision, Recall, and F1-score. The hybrid model achieved the highest performance with 98% in all metrics. In contrast, the Gradient Boosting model had the lowest performance, with an Accuracy of 91%, Precision of 92%, Recall of 90%, and F1-score of 91%, indicating it is less suited for dynamic throughput prediction tasks. A visual representation of the overall accuracy of the models is provided.

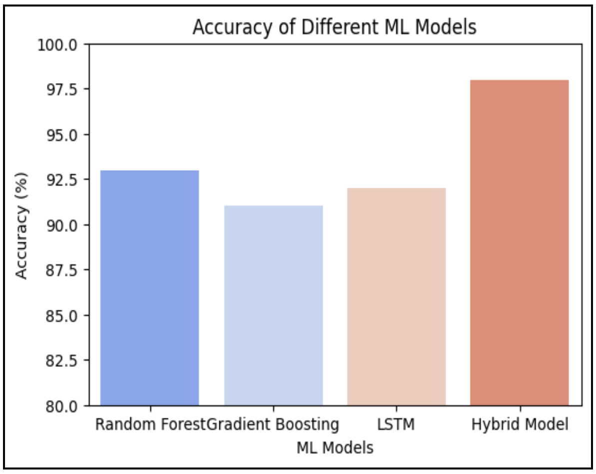

Fig 8 Accuracy of Different Ml Models

Finally, the results suggest that the hybrid model is going to be the best model for the prediction of throughput in 5G networks, with an Accuracy of 98%, Precision of 98%, Recall of 98%, and F1-score of 98%. As compared with other models, they have lower performance than the hybrid model, mainly the Gradient Boosting model, which is poor in terms of ac curacy with 91%, Precision with 92%, and Recall with 90%, and F1-score of 91%, which is not suitable for dynamic throughput prediction. So the results suggest that the hybrid model is going to be the best model for the prediction of throughput in 5G networks, which helps network engineers to optimize network resources and enhance user experience.

Below is the visual representation of all other performance metrics like Precision, Recall, and F1-score of the various machine learning models we developed.

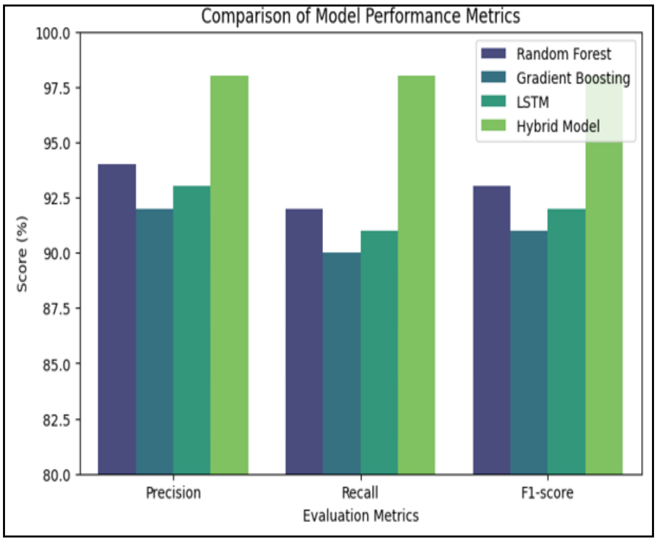

Fig 9 Comparison Of Model Performance Metrics

Table IV Shows the Comparison of The Previous Model's Accuracy With The Proposed Model.

Related work	**Models**	**Accuracy**
Harsh Agrawal et al.	Transfer learning and data augmentation	96%
Israa F. Jassam et al.	LSTM	93%
M. Kavitha et al.	CNN	89%
Blida Montalico et al.	Random Forest	89%
Chilukuri Pavan Chowdary et al.	VGG-16	86%
Proposed Work	Hybrid Model	98%

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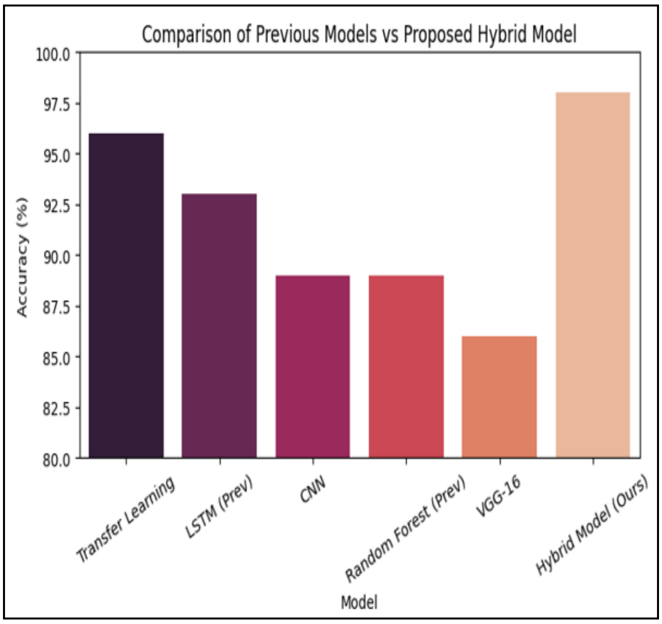

Fig 10 Comparison of Previous models with current model

Ultimately, our results indicate that the hybrid model achieved the highest accuracy on the dataset, with a score of 98%. The other models performed on the dataset as follows: Random Forest with 93%, Gradient Boosting with 91%, and LSTM with 92% Accuracy rates. These results suggest that the hybrid model is going to be the preferred one for the prediction of throughput in 5G networks, which helps in optimizing network resources and enhancing user experience.

VI. CONCLUSION

This study emphasizes how crucial precise throughput prediction is for 5G networks, especially for improving user experience and network resource optimization. Maintaining constant throughput is extremely difficult with 5G networks due to its dynamic nature, which is typified by shifting network circumstances and variable user demands. Using an extensive dataset of 5G networks, we carefully assessed a number of cutting-edge machine learning models in this study, such as Random Forest, Gradient Boosting, LSTM, and a hybrid model. Our results showed that the hybrid model outperformed the other models in dynamic throughput prediction with an exceptional accuracy of 98% because to its better design, which combines Random Forest and LSTM. This high degree of precision demonstrates how the hybrid model has the ability to greatly improve network management skills, allowing network engineers to maximize resources and improve user experience. These findings have significant ramifications, indicating that the administration of 5G networks may undergo a radical change if sophisticated machine learning models are integrated into network management systems. Better resource allocation, lower latency, and more effective use of network resources can result from this. Additionally, the hybrid model's strong performance offers a strong basis for next studies that will focus on improving and enhancing machine learning models for 5G network administration.

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