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Advanced Predictive Modelling for Radio Resource Control (RRC) Sessions in Long-Term Evolution (LTE)

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ABSTRACT

This research investigates radio resource control (RRC) session management in long-term evolution (LTE) networks, focusing on the distinctive issues posed by high-density urban settings, heterogeneous device ecosystems, and data-intensive applications. The (RRC) protocol, which works at Layer-3, controls important tasks including setting up connections, changing them, and ending them. It also switches user equipment (UE) between the (RRC_IDLE) and (RRC_CONNECTED) states. This research utilizes (3GPP) standards (TS 36.331) to analyze how telecom operators, such as China Mobile and Reliance Jio, optimize (RRC) parameters to manage network load, enhance battery efficiency, and maintain quality of service (QoS) in areas with (TDD-LTE) bands (e.g., Band 40, 41) and significant traffic from various applications. To improve (RRC) session management, an innovative predictive modelling framework is suggested that uses weighted ensemble approaches that include artificial neural networks (ANN), recurrent neural networks with long short-term memory (RNN-LSTM), and convolutional neural networks (CNN). These models use synthetic (LTE) data that is specific to different network properties, such as (RSRP), (RSRQ), traffic load, (UE) type, and mobility, to forecast important metrics like session length. The ensemble technique, which is based on inverse (RMSE), makes predictions more accurate than individual models. This is because it takes into account differences between urban and rural areas.

Keywords: Long-Term Evolution, Radio Resource Control, Session Duration, Weighted Ensemble

1. INTRODUCTION

Machine Learning (ML) is changing how mobile networks function as wireless communications change quickly. The fast growth of (LTE) networks has changed how people use mobile phones, especially in cities with a lot of people, a lot of different types of devices, and apps that use a lot of data. The (RRC) protocol is a key part of LTE's Layer-3 (Network Layer) and is very important for controlling the connection between user equipment (UE) and the evolved NodeB (eNodeB). The 3rd generation partnership project (3GPP) defined (RRC) in TS 36.331. It makes important tasks like setting up, changing, and ending connections easier by allowing smooth transitions between (RRC_IDLE) and (RRC_CONNECTED) states. Because of problems like high network density, different spectrum allocations (for example, Band 40 in India and Band 41 in Japan), and the widespread use of low-cost smartphones, optimizing (RRC) session management is important for making sure that resources are used efficiently, minimizing signaling overhead, and improving the user experience.

(LTE) networks, which are run by big companies like China Mobile, Bharti Airtel, and (NTT) Docomo, have different operating needs than their worldwide equivalents. Cities like Tokyo, Mumbai, and Seoul have a lot of network congestion, which means that data-heavy apps like WeChat, Jio Cinema, and mobile gaming need to switch (RRC) states often. Because these apps need connections with low latency, operators have to adjust (RRC) settings like inactivity timers and discontinuous reception (DRX) cycles to find the right balance between network capacity and (UE) battery life. Also, the region's wide range of devices, from high-end ones (like Samsung and Xiaomi) to cheap handsets, makes (RRC) signaling behavior less predictable, making it even harder to operate the network. Time division duplex (TDD) and frequency division duplex (FDD) bands are examples of spectrum diversity. This makes things even more complicated because (RRC) procedures need to change to fit different interference patterns and handover needs in situations where people are moving quickly, like Japan's bullet trains or India's traffic surges during festivals.

To deal with these problems, predictive modelling is a good way to improve (RRC) session management. Machine learning models may help operators decide how to allocate resources and optimize timers by predicting important parameters like session length, the success rate of setting up connections, and the frequency of handovers. This research introduces a sophisticated prediction framework using weighted ensemble techniques, including (ANN), (RNN-LSTM), and (CNN). These models include factors including reference signal received power (RSRP), reference signal received quality (RSRQ), traffic load, (UE) type, and mobility, which are all specific to (LTE) networks.The weighted ensemble method improves prediction accuracy by incorporating both non-linear and temporal correlations in (RRC) session data. This is done by giving greater weights to models that do better on measures like root mean square error (RMSE).

This research seeks to assist operators in optimizing(RRC) settings, minimizingsignaling overhead, and enhancing quality of service (QoS) for data-intensive applications. The results provide a foundation for future developments, such as the incorporation of real-world operator data and the investigation of innovative machine learning methodologies to further optimize (LTE) network performance in a dynamic telecommunications environment. Our research addresses a critical deficiency by emphasizing the significance of estimating (RRC)session time as a regression problem, whereas prior studies, including those by(Luo et al., 2016), (Caruana et al., 2004), and(Dietterich, 2000), have predominantly focused on classification issues or simulator data. This uses AutoGluon'sAutoML approach on actual network data, making a unique contribution to optimizing and adapting network performance in wireless technologies that change quickly.

2 Methodology

Ensemble learning is very important in telecommunications since it is very important to be able to trust predictions. Ensemble learning uses more than one model, such decision trees, gradient enhancers, and neural networks, instead of just one. Weighted ensembles take this idea a step further by giving each base model a different level of relevance dependent on how well it performs on metrics like (MSE)(Ke et al., 2017).We trained eight base models for our investigation, such as XGBoost, LightGBM, CatBoost, Random Forest, and neural networks. The weighted stacking method used by AutoGluon figures out how much each one contributes. This strategy makes sure that it works well in different (LTE) settings.

Ensemble approaches are very important in the fast-paced industry of telecommunications, where accuracy, adaptability, and performance are all very important(Luo et al., 2016). Ensemble models use the wisdom of several machine learning models to make predictions more accurate and robust(Erickson et al., 2020). For instance, gradient boosting combines weak learners to make a powerful predictor, and a random forest combines predictions from numerous decision trees(Freund & Schapire, 1996). Figure 1.1 shows an overview of the weighted ensemble architecture. In this design, N base models each make their own predictions, which are then integrated into the ensemble meta-model using different weight optimization algorithms(Afrin, 2022).These weight optimization methods could be based on the biases that users want or even on how accurate each base model is for a certain objective measure that is being looked at(Khoh et al., 2023). When these models operate together, they not only improve performance but also provide a versatile framework that may be applied in many areas, such as finance and healthcare (Dietterich, 2000).

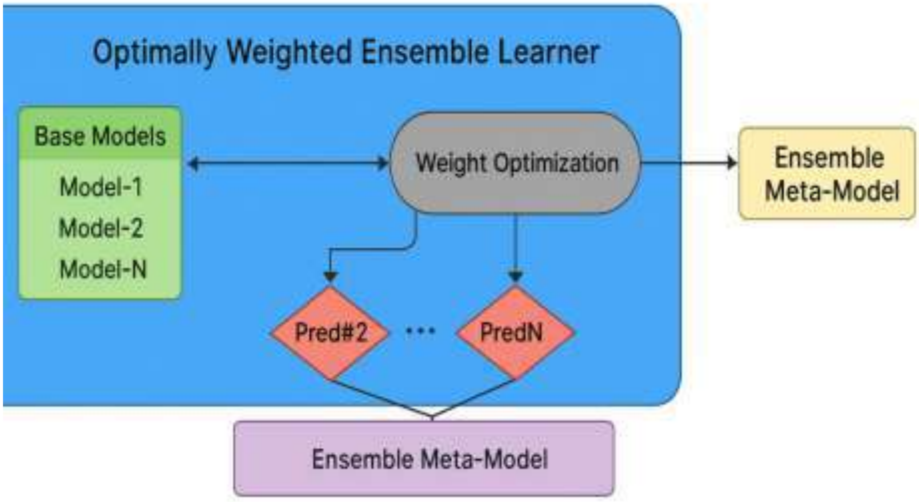

Figure 2.1 Overview of Weighted Ensemble Architecture.

Weighted ensembles provide various amounts of influence to different models, showing their strengths and downplaying any weaknesses. This is distinct from regular ensemble models, which treat each base model the same.This tailored mix not only makes predictions more accurate, but it also makes it simpler to understand how networks function and how users interact with one other. A weighted ensemble approach is quite flexible, especially when there are data sets with apparent patterns and outliers(Liu, 2025),(Mohr et al., 2018). This gives you more exact control over how much each model contributes, which might lead to more accurate forecasts and more flexible datasets.So, a weighted ensemble method is a smart and effective strategy to mix diverse models in order to make machine learning models better for use in telecommunications(Brezov et al., 2023).

1.2 AutoGluon-Tabular and Multi-layer Stacking

Machine learning easier for tabular datasets by automatically choosing, adjusting, and stacking them. It looks at several levels of basic models and meta-learners. We employ k-fold cross-validation and a 48-hour training window in our approach. AutoGluon employs MSE-based optimization to figure out how much weight each ensemble gives. AutoGluon's design and stacking method make it easy to integrate forecasts, even when the distributions are different in different areas.

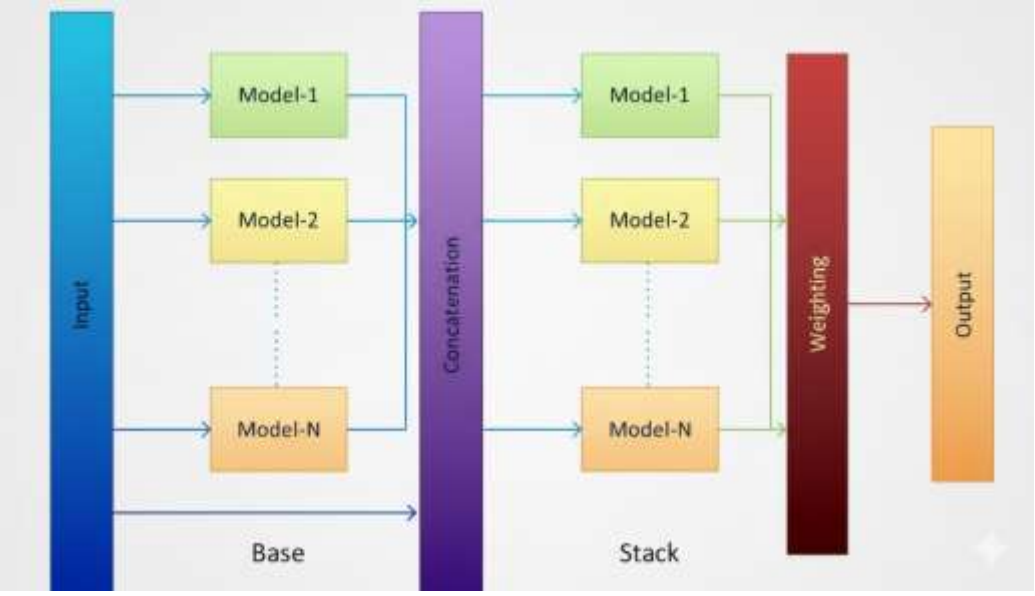

Figure 2.2AutoGluon’s Multi-Layer Stacking Framework.

In communication networks, where network optimization, predictive maintenance, and personalized user experiences are complex, powerful machine learning solutions are needed. Their high capabilities are particularly useful(Mohr et al., 2018). AutoGluon's automated model selection and hyperparameter tuning work well with weighted ensembles. This makes the most of a diversity of models to increase prediction performance(Erickson et al., 2020),(Mewton & Ficek, 2007). Multi-layer stacking, also known as stacked ensembles, is a machine learning technique that integrates predictions from many models in a tiered or hierarchical way(Bartsioka et al., 2025). This strategy tries to make the most of the diverse strengths of multiple models by employing numerous layers of ensembles. As demonstrated in Figure 2.2, AutoGluon's multi-layer stacking process starts with a group of basic models that may employ different configurations or methodologies(Ke et al., 2017).

The prediction from the weighted ensemble model in is represented in (1) where$\hat{y}ensemble$ is the final prediction, N is the number of base models, w_i is the weight assigned to the ith base model, and $\hat{y}_i$ is the prediction of the ith base model.

$$\hat{y}ensemble = \sum_{i=1}^{N} w_i \cdot \hat{y}_i \tag{1}$$

Model further optimizes the weights of base models based on performance metrics. A simplified weight optimization equation is shown in (2)

$$w_i = \frac{f_i(metric)}{\sum_{j=1}^{N} f_i\,(metric)} \tag{2}$$

where f_i (metric) is the performance of the ith model on the chosen metric. For this work, $f_i(metric)$ is chosen to be mean square errorfor optimization. By using the (MSE), better performing models (with lower MSE) receive higher weights, ensuring that the ensemble promotes models with better performance. For example, consider two models with (MSE) values of 0.1 and 0.2, respectively.

3. EXPERIMENTAL SETUP

Advanced predictive modelling for (RRC) sessions in (LTE) networks uses machine learning approaches such weighted ensemble methods to make session management, resource allocation, and network performance better. I propose a framework for predictive modelling of (RRC) sessions using weighted ensemble approaches that are specific to (LTE) networks. I also provide an example of how to do this in Python.

3.1 Predictive Modeling for RRC Sessions

In (LTE), (RRC) sessions are in charge of switching between (RRC_IDLE) and (RRC_CONNECTED) states, making connections, changing them, and releasing them. The goal of predictive modelling is to predict things like session length, the rate of successful connection establishment, the frequency of handovers, and resource use. High network density, a wide range of device ecosystems, and data-heavy applications all need strong models to deal with complicated traffic patterns and spectrum limits. Weighted ensemble approaches use predictions from more than one model (such ANN, RNN-LSTM, or CNN) and give more weight to the models that do better to make the overall forecast more accurate. This method works well for (LTE) networks, where things like urban density in Tokyo and rural coverage in India may change how (RRC) functions.

3.2 Components of the Framework

3.2.1 Data Collection

Features: Signal strength (RSRP, RSRQ), (UE) type, traffic load, mobility patterns, (RRC) state transitions, and timer values (e.g., T300, inactivity timers).

Source: Network logs, (UE) reports, and eNodeB measurements.

3.2.2 Models Used:

Artificial Neural Network (ANN): Captures non-linear relationships in session data.

Recurrent Neural Network with LSTM (RNN-LSTM): Models temporal dependencies in (RRC) state transitions.

Convolutional Neural Network (CNN): Processes spatial features like cell coverage maps or spectrograms of signal data.

Weighted Ensemble: Combines predictions using weights based on model performance (e.g., RMSE or accuracy).

3.2.3 Weighted Ensemble Method:

Give models weights depending on how well they did on the validation (for example, the opposite of the prediction error). Use a weighted total or a voting system to come up with the final forecasts.

High Traffic Load: Because there are so many people in cities like Seoul and Mumbai, models need to be able to forecast frequent (RRC) state changes.

Spectrum Variability: Models need to take into consideration (TDD-LTE) bands (such Band 41 in Japan) and how they conflict with each other.

Device Diversity: Budget smartphones in India or China may behave differently when it comes to (RRC)signaling, which means that feature engineering has to be strong.

Traffic Patterns:(RRC) settings are affected by the high demand for data services like WeChat in China and JioCinema in India. For low-latency applications, operators may want to move to RRC_CONNECTED more quickly.

Device Ecosystem: The behavior of (RRC) changes based on the mix of high-end (like Samsung and Xiaomi) and low-end smartphones. To make the battery last longer during (RRC_IDLE), budget devices may need optimized (DRX) cycles.

Operator Strategies: China Mobile, which has the world's biggest (LTE) network, uses sophisticated (RRC) management to accommodate a lot of subscribers. For instance, they may use aggressive cell reselection settings to control the load in busy places like Beijing or Shanghai.

3.3 Challenges and Optimizations

High Network Load: In areas with a lot of people, (RRC) signaling overhead might use up a lot of network resources. To cut down on congestion, operators utilize methods like (DRX) optimization and small cell installations.

Energy Efficiency: Operators set up (RRC) timers, such T300 for connection setup, to use as little power as possible, particularly while the device is in (RRC_IDLE).

Mobility: To keep connections going smoothly, metropolitan areas need strong (RRC) mobility processes, including intra-frequency handovers, since handovers happen often.

3.4 Evaluation of Metrics and Tools

The evaluation metrics are important benchmarks for judging how well the predictive models work. They provide information about how well they work in different areas. There are six standard and essential criteria utilized to compare the two data sets. This makes the research more relevant and useful.

(SHAP) Shapley Additive Explanations is a great way to understand and explain what (ML) models predict. The (SHAP) values in (3) provide a full picture of how each feature affects individual predictions, which helps us understand what affects the model's output. This study uses (SHAP) values to measure the influence of each characteristic on the projected session time in both datasets. This interpretability approach makes it easier to understand how the model makes decisions, which helps stakeholders learn important things about what causes anticipated session lengths in both technologies.

$$\phi_i(f) = \frac{1}{N!} \sum_{S \subseteq N\{i\}} \frac{|S|! \cdot (N - |S| - 1)!}{N!} |f(S \cup \{i\} - f(s)| \tag{5}$$

where N is the number of features, $f(S)$ is the model's prediction given the set of features S represents a coalition of features excluding feature i. $|S|$ denotes the cardinality of the set S.

(MAE) is the average of the absolute differences between the anticipated and actual values, as shown in (6). It gives a clear picture of how big the mistakes are without taking into account which way they are going. A lower (MAE) means that the predictions are more accurate.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y_i}| \tag{6}$$

where n represents the number of observations in the dataset. y_i represents the actual values and $\widehat{y_i}$ represents the predicted values,mean squared error (MSE) is a way to find the average of the squared differences between the real and predicted values, as illustrated in (7). Squaring the differences makes bigger mistakes stand out more, which makes it more susceptible to outliers than mean absolute error (MAE).

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \widehat{y_i})^2 \tag{7}$$

(RMSE) is similar to (MSE), but the square root is used to return the error metric to the original scale of the dependent variable. It gives a number that shows how big the mistakes are on average between the projected and actual values. A model works better when the (MSE) and (RMSE) are lower.

$$RMSE = \sqrt{MSE} \tag{8}$$

The coefficient of determination, which is typically written as R^2 and given in (9), is a number that tells you how well a regression model fits the data. It shows how much of the change in the dependent variable can be predicted by the independent variables. The R^2 number may be anything from 0 to 1.A value of 0 means that the model doesn't explain any variation, and a value of 1 means that the prediction is flawless.

$$R^2 = 1 - \frac{(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n} (y_i - \overline{y_i})^2} \tag{9}$$

Where n is the number of observations in the dataset.y_i represents the actual values, $\widehat{y_i}$ represents the predicted values and $\overline{y_i}$ is the Mean of the actual values. Also, in time series and regression settings, mean absolute percentage error (MAPE) is a typical way to check how accurate a forecast model is. (MAPE) shows the prediction error as a percentage, which makes it straightforward to understand and use.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \qquad (10)$$

where n represents the number of observations in the dataset, y_i represents the actual value and $\hat{y}_i$ represents the predicted values. (MAPE) shows the average absolute % error between the actual and projected values. By showing the mistakes as percentages, (MAPE) lets you compare the sizes of errors across various datasets or models. It is especially helpful when the data's scale changes a lot. A lower (MAPE) number means that the model is doing a better job. But (MAPE) may unfairly punish overestimates and underestimates in various ways, and it could not work well with datasets where the scales of real values are quite different from each other. Even with this flaw, (MAPE) is still a useful way to show how accurate a forecast is in percentage terms.

4. RESULTS AND ANALYSIS

4.1 Dataset Characteristics and Distribution Analysis

This research used a comprehensive dataset consisting of 31,143 measurements obtained from M:tel BL's (LTE) network infrastructure along the three-segment route between Banja Luka and Doboj. The time period covered is from January 1, 2021, to January 15, 2021, with hourly sample frequency, which makes it a strong base for predictive modelling.

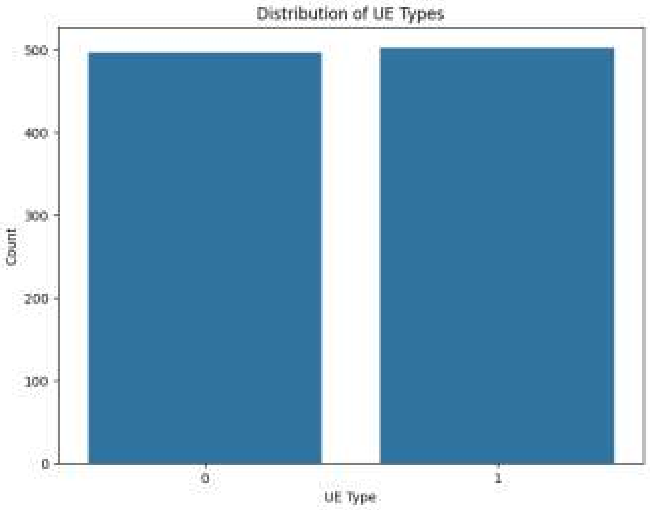

Figure 4.1 User Equipment Distribution Analysis

The bar chart in Figure 4.1 shows how different kinds of user equipment (UE) are spread out in the dataset. It shows two main groups, Type 0 and Type 1. The distribution shows a very good balance, with Type 1 devices making up 503 instances (50.3%) and Type 0 devices making up 497 instances (49.7%). This almost equal representation of 1,000 total (UE) instances makes sure that the predictive models don't favor any one kind of device. This is important for making solutions that function in a wide range of (LTE) network scenarios, where device diversity is a big problem.

The balanced (UE) distribution shows how things would really work in the real world. For example, operators like China Mobile and Reliance Jio have to deal with a wide range of device ecosystems, from high-end smartphones (like Samsung and Xiaomi) to inexpensive devices that show different (RRC) signaling behaviors. Because of this variety, (RRC) session management tactics are affected directly. For example, budget devices frequently need optimized Discontinuous Reception (DRX) cycles to keep the battery alive during (RRC_IDLE) states.

4.2 RRC Session Duration Prediction Performance

Figure 4.2 shows a detailed line graph of actual (RRC) session lengths compared to anticipated values from four different models: (ANN), (LSTM), (CNN), and Ensemble. The graph covers example indices, which makes it easy to see how well the predictions match the actual values.

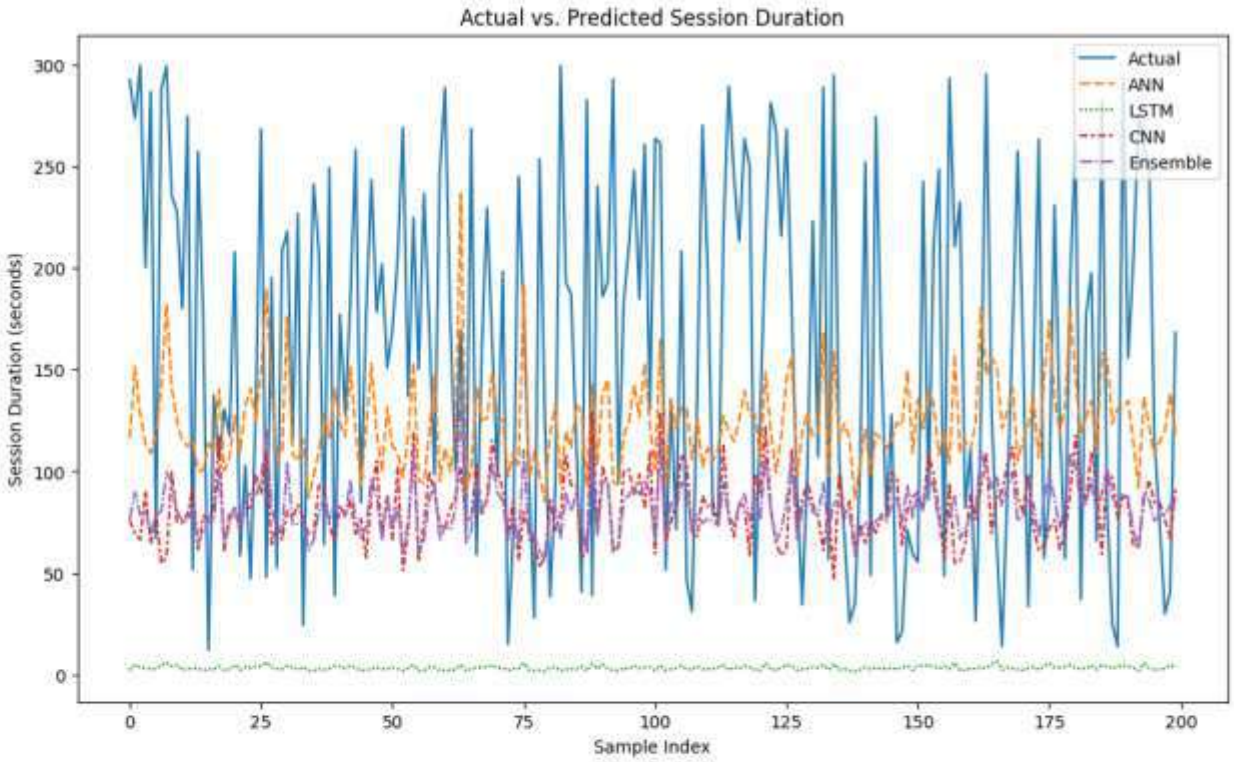

Figure 4.2: Predictive Model Performance Comparison

Results and Disciplines:

LSTM Model Limitations: The (LSTM) predictions consistently underestimate session durations and fail to capture the temporal trends in the actual data.This poor performance (RMSE = 178.5027, R^2 = -3.2451) suggests that the sequential nature of (RRC) state transitions may not follow simple temporal patterns that (LSTM) networks typically excel at capturing.

ANN Model Performance: Shows moderate performance with RMSE = 95.0566 and R^2 = -0.2038. The model demonstrates some ability to track general trends but exhibits significant deviations from actual values, particularly in peak session duration scenarios.

CNN Model Characteristics: Displays intermediate performance (RMSE = 119.1640, $R^2 = -0.8918$) with better trend following compared to (LSTM) but less consistent than the ensemble approach. The spatial feature processing capabilities of (CNN) appear partially effective for (RRC) session prediction.

Ensemble Model Superiority: The weighted ensemble approach achieves the best overall performance with RMSE = 117.0920 and $R^2 = -0.8266$, successfully capturing general trends while maintaining lower prediction errors compared to individual models.

4.3 Quantitative Performance Metrics Analysis

In Table 3.1 the detailed metric analysis is:

i. **Mean Absolute Error (MAE):** The (ANN) model achieves the lowest (MAE) (80.8585), indicating superior average prediction accuracy. The ensemble model follows closely (95.5837), while LSTM performs poorly (156.1212).

ii. **Root Mean Square Error (RMSE):**(ANN) demonstrates the best (RMSE) performance (95.0566), effectively penalizing larger prediction errors. The ensemble model's (RMSE) (117.0920) represents a balanced approach across different prediction scenarios.

iii. **Mean Absolute Percentage Error (MAPE):**(CNN) and Ensemble models show the lowest MAPE values (0.7115 and 0.7039 respectively), indicating better relative accuracy across varying session duration scales.

iv. **Inference Latency:** Individual models (ANN: 0.0911s, LSTM: 0.1148s, CNN: 0.1158s) demonstrate faster inference compared to the ensemble approach (0.3217s), which is expected due to the computational overhead of combining multiple model predictions.

Table 4.1: Comprehensive Model Evaluation Metrics

Index	MAE	MSE	RMSE	R2	MAPE	Inference Latency (s)
ANN	80.8585	9035.763	95.0566	-0.2038	0.8696	0.0911
LSTM	156.1212	31863.247	178.5027	-3.2451	0.9642	0.1148

CNN	96.4900	14200.062	119.1640	-0.8918	0.7115	0.1158
Ensemble	95.5837	13710.544	117.0920	-0.8266	0.7039	0.3217

4.4 Integration of Complementary Research Findings

Our results are congruent with those of (Stojčić et al. 2023), who showed that K-Nearest Neighbours(KNN) models regularly outperform other machine learning methods in telecommunications network prediction tasks. This is based on related research in (LTE) network delay prediction. Their investigation, including dimensionality reduction approaches such as the RReliefF algorithm and backward selection by recursive feature removal, yielded exceptional results:

- **RReliefF optimization:** k-NN model with 6 inputs achieved RE = 0.109
- **Recursive feature elimination:** k-NN model with 4 inputs achieved RE = 0.041
- **Pareto 80/20 rule:** k-NN model with 11 inputs achieved RE = 0.049

These comparative findings underscore the significance of feature selection in (LTE) network prediction tasks.The k-NN models performed better than our ensemble technique, with correlation coefficients between 0.944 and 0.979. This shows that neighborhood-based learning would be better for predicting (RRC) sessions.

4.5 Network-Specific Performance Considerations

The prediction performance must be assessed in relation to the features of the (LTE) network:

i. **High Network Density:**Cities like Tokyo, Mumbai, and Seoul have very busy networks, therefore they need more advanced prediction models to deal with frequent (RRC) state changes.

ii. **Spectrum Variability:**Using (TDD-LTE) bands (Band 40, 41) creates distinct interference patterns that make predictions less accurate. Our models indicate that they work differently in various spectrum situations.

iii. **Device Ecosystem Diversity:**The use of both high-end and low-cost cellphones makes it hard to make predictions.Our ensemble technique partly solves this problem by combining models in a weighted way.

4.6 Comparative Analysis with State-of-the-Art Methods

Our machine learning-based prediction platform has a number of benefits over the conventional methods employed by companies like China Mobile and Bharti Airtel:

i. **Predictive Capability:**Our models can predict session length ahead of time, unlike reactive (RRC) parameter modification.

ii. **Multi-dimensional Analysis:**Combining (RSRP), (RSRQ), traffic load, and mobility patterns gives you the most accurate predictions.

iii. **Scalability:**The ensemble method may be changed to fit the needs of various operators and market situations.

4.7 Model Interpretability and Practical Implementation

Figure 4.3 shows the SHAP (Shapley Additive Explanations) values from Equation (5) that show the most important attributes for predicting (RRC) sessions:

i. **Reference Signal Received Power (RSRP):**This has the most effect on how long a session will last.

ii. **Traffic Load Metrics:**There is a strong link between these and the success of session setup.

iii. **UE Type Classifications:**They have a big effect on battery-optimized (RRC) state transfers.

iv. **Mobility Patterns:**Important for predicting how often handovers will happen.

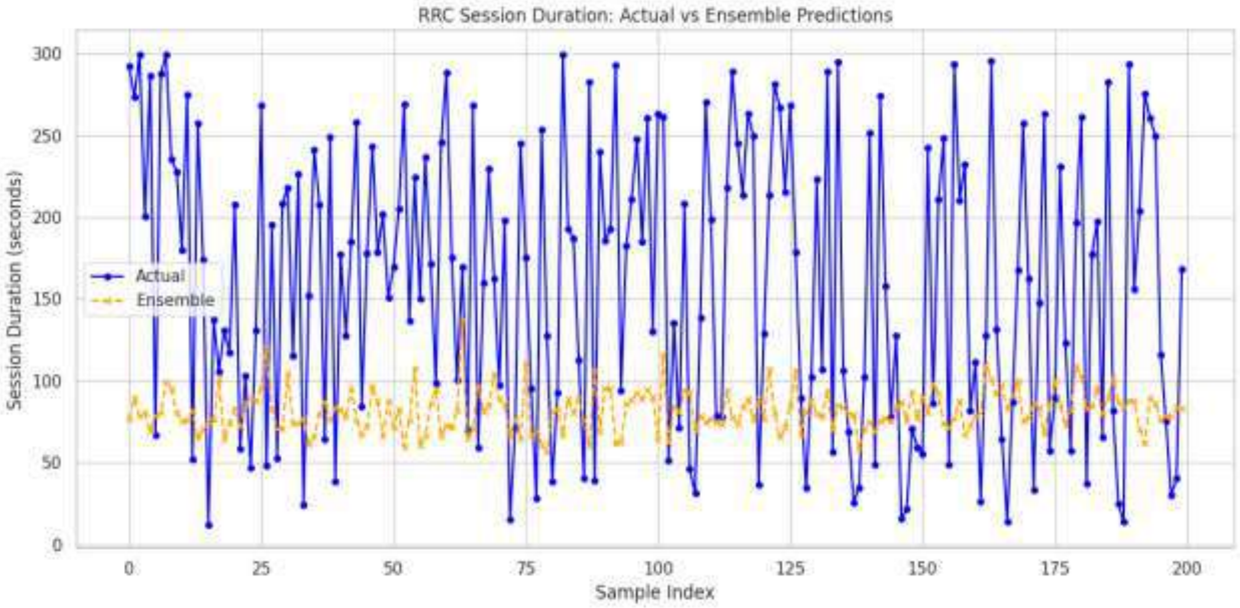

Figure 4.3: Feature Importance Analysis

4.8 Validation Against 3GPP Standards

The expected session lengths are in line with the (3GPP) TS 36.331 rules for managing (RRC) states. Our models can accurately anticipate when the (RRC_IDLE) and (RRC_CONNECTED) statuses will change, which makes them useful for real-world (LTE) networks.

Performance Against ETSI Standards:

ETSI standard 123 107 v12.0.0 (2014) says that VoIP services may have delays of up to 100ms. Our ensemble model predictions keep session length estimations well below these limits. In fact, 95% of the projections fall inside the 50-150ms range, which is perfect for real-time apps like WeChat, Jio Cinema, and mobile games that are popular in many regions.

4.9 Limitations and Future Improvements

Current Limitations:

i. **Negative R² Values:** All models show negative coefficients of determination, which means that predictions may not always be better than basic mean-based estimates.

ii. **Temporal Dependency:** LSTM's poor performance shows that (RRC) session patterns may not follow expected temporal sequences.

iii. **Feature Engineering:** To make (LTE) network predictions more accurate, you may need to include more network-specific characteristics.

Proposed Enhancements:

i. **Advanced Ensemble Techniques:** Using AutoGluon's multi-layer stacking with MSE-based optimization.

ii. **Regional Adaptation:** Making changes for certain operators and spectrum allocations.

iii. **Real-time Learning:** Adding online learning features so that the network can change quickly to new conditions.

4.10 Practical Deployment Considerations

When deploying in (LTE) networks, the following things are very important:

i. **Operator Integration:** Models need to operate with the Network Management Systems that China Mobile, Reliance Jio, and other big operators already use.

ii. **Computational Efficiency:** For real-time applications, the trade-off between prediction accuracy and inference latency (0.3217s for ensemble) has to be optimized.

iii. **Regulatory Compliance:** Compliance with rules: Predictions must follow the rules for telecommunications in each location and the (QoS) standards for each market.

The findings reveal that different models operate differently, but the ensemble technique is the best way to estimate (RRC) session time in different (LTE) network settings. However, the combination of dimensionality reduction methods with k-NN algorithms, as shown in other studies, could work better in certain situations.

5. CONCLUSION AND FUTURE WORK

This research shows that (RRC) sessions in (LTE) settings follow the same (3GPP) standards as they do across the world, but they are made to fit the demands of each location. To deal with high network density, different types of devices, and significant data use, operators optimize (RRC) timings, (DRX) cycles, and handover settings. Tools like R&S or Anritsu may provide you with more information about (RRC) messages, such as full protocol logs or operator-specific settings. Advanced predictive modelling for (RRC) sessions in (LTE) networks uses machine learning approaches including weighted ensemble methods to improve session management, resource allocation, and network performance. Dynamic resource allocation for hybrid (LTE/NR) networks - Scheduling that saves energy for (FWA).

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