# Predicting Channel Quality Indicator (CQI) in LTE Using Ensemble Learning Approaches

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**Abstract**

*Correct prediction of Channel Quality Indicator (CQI) is a key to successful link adaptation and resource allocation in Long-Term Evolution (LTE) and 5G New Radio (NR) networks. The paper presents a CQI prediction method based on an ensemble-based technique by using measurements on the LTE radio signals like Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Received Signal Strength Indicator (RSSI), and Signal to Noise Ratio (SNR). The proposed method is evaluated against with individual machine-learning models since it combines complementary learners to improve prediction stability and accuracy. Result obtained from publicly available datasets of LTE show the proposed framework outperforms other competitors with an MAE of 0.66 and $R^2$ of 0.93. The ensemble would add to training and inference time, but prediction latency per sample (0.052 ms/sample) is much lower than LTE timing requirements, and thus quite practical to use in real time. In general, this work demonstrates that an ensemble-based method can provide a significant boost to the efficacy of CQI estimation, which can become a promising solution to effective scheduling and adaptive modulation of LTE systems.*

**Keywords**: ***Channel Quality Indicator, LTE, ensemble learning, stacking, machine learning, link adaptation, CQI prediction***.

## Introduction

Reliable Channel Quality Indicator (CQI) estimation is fundamental to efficient link adaptation, resource allocation, and modulation and coding selection in Long-Term Evolution (LTE) systems. Accurate CQI ensures that base stations select appropriate transmission parameters necessary for maintaining Quality of Service (QoS). In contrast, inaccurate or delayed CQI reporting leads to retransmissions, throughput degradation, and poor user experience, especially under fast-varying wireless conditions.(Elsherbiny et al., 2020; Rappaport, 2013).

LTE Traditional CQI estimate is founded on user equipment direct recording and reporting. Though effective, such methods can be ineffective in situations where fading is rapid, produce feedback load, and cannot rely on historical and contextual signal patterns. Consequently, learning-based approaches have achieved popularity since they could deduce CQI by using signal-quality measures that are measurable to the observer and nonlinear trends that are neglected by conventional estimators (Cordina & Debono, 2017; Vankayala & Shenoy, 2020). The literature such as Osiezagha, Mishra, and Fagbola (2025), Kim and Han (2023) are mainly about individual machine-learning models such as regression-based predictors, tree-based, or neural networks that demonstrate good results but are not very robust and generalized under different channel conditions. It is the gap, however, in building a framework that will not only increase accuracy, but also guarantee a consistent performance of prediction across situations.

To settle this, the current paper proposed a stacking-based ensemble model of CQI prediction and compared that with commonly used single learning models. The significant findings of this paper are:

1. Comparison of several machine-learning models based on publicly available LTE datasets.
2. establishment of a stacking group of learners that are complementary to each other and will be used to augment the robustness of CQI predictions.
3. performance evaluation based on accuracy and computational issues, and
4. evidence that the proposed ensemble is capable of enhancing prediction accuracy, but does not increase inference latency beyond the LTE timing constraints, which can be applied in real-time.

**Literature Review**

Machine learning is another widely used tool in predicting communication quality metrics of wireless network. The first methods used statistical techniques and rudimentary machine learning to predict Channel Quality Indicator (CQI) or similar measures, but tended to fail in nonlinear channel behavior and dynamic conditions (Soret et al., 2015). New developments prove that more advanced models can be used to capture more complex relationships between radio signal features and CQI.

Ensemble models like Random Forest and Gradient Boosting have been used in several studies like Pavan, M., & Reddy, B. R. (2022), Yang, Y., Zhang, H., Wang, W., and Li, Z. (2022), and have helped in quality prediction of wireless better than simple models. Nevertheless, these techniques continue to suffer a scaling or generalization deficit in a wide range of channel scenarios. In a few studies, ensemble-based models have been used to predict the quality of a wireless.

Okiemute Osiezagha et al. (2025) investigated supervised ensemble algorithms in the prediction of mobile network coverage and signal quality and found a better performance compared to that of single learners. Nevertheless, they concentrated on estimation of coverage in a university level test setting, but not CQI regression in a variety of LTE conditions. Similarly, Sharma et al. (2025) used machine learning to predict and optimize channel quality in 5G, indicating that learning based methods can be used to increase the accuracy of predictions. They however did not investigate stacked meta-learning strategies or latency in-depth scrutiny of real-time applicability in their study.

Bakri et al. (2020) established channel stability prediction using deep learning in 5G with a heavy emphasis on the flexibility to changing time-dependent wireless conditions. Most recently, Kim and Han (2023) designed a CNN, LSTM based CQI prediction model in vehicular communication and demonstrated an improvement in accuracy through the model with the help of temporal information. On a similar note, Ahmad (2025) developed a CQI prediction technique unique to 5G NR by comparing SNR to CQI mapping, but on a small scale, to one model and network condition, but it primarily focused on the design of algorithms as opposed to comparison of the models as families or trade-offs between computation and cost.

However, despite the research into deep learning and ensemble-based methods of CQI prediction in LTE systems, much of the current literature still adopts individual models, including CNNs or LSTMs, or simple ensemble strategies of averaging predictions. These approaches do not exploit the opportunities of integrating various categories of learners within one frame to the fullest. Moreover, previous research has mostly focused on the accuracy of prediction but rendered little focus on the training complexity and inference delay despite the fact that they are important in real-time scheduling and link adaptation in LTE networks. As a result, the literature on the use of stacked ensemble models to perform CQI prediction that combine a variety of base learners and are not only assessed based on their accuracy but also the appropriateness to use in real-time application has a distinct gap.

The gap that is filled in the current study is the suggestion of a stacking-based ensemble framework that uses any type of models such as gradient boosting models and neural networks to boost robustness and generalization. In contrast to the previous literature where either a deep learning approach was considered or the ensembles were not supplemented by any meta learning, the study measures the predictive performance and the computational efficiency to determine the feasibility in LTE transmission timing budgets. This puts the contribution as a viable and scalable solution towards real-time CQI prediction and adaptive modulation strategies in LTE systems.

## METHODOLOGY

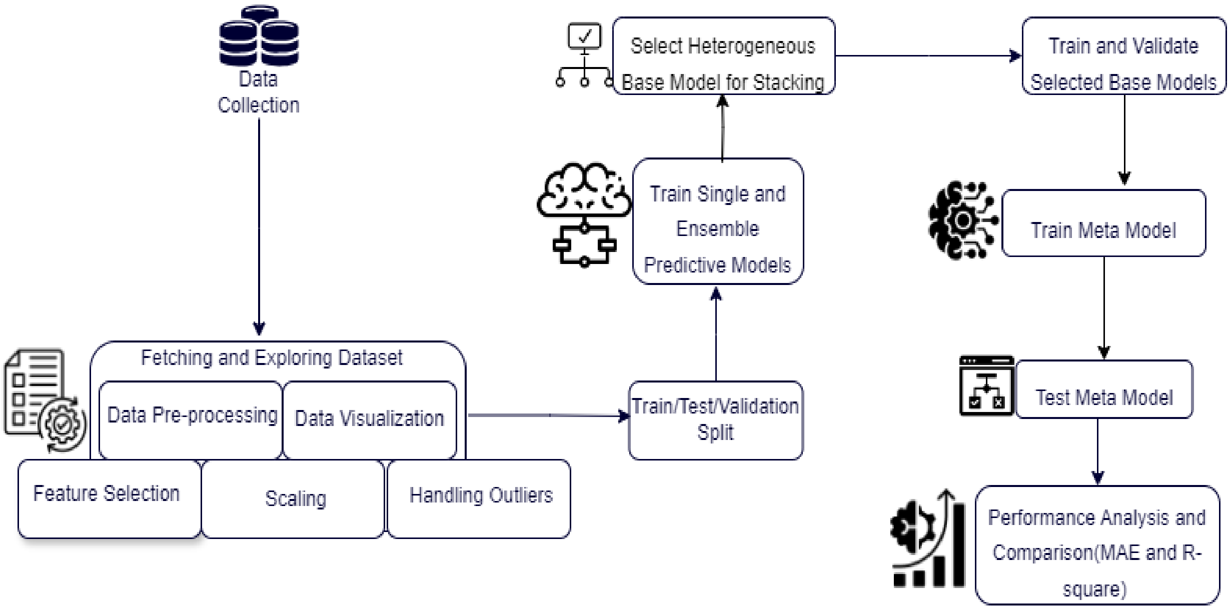


*Figure 1: Block diagram of Research Methodology*

### Dataset

Kaggle made two publicly available datasets of LTE to train and test predictive models of Channel Quality Indicator (CQI). Netflix_v0 Dataset has 34,709 records of network measurements of video streaming. It includes such features as Timestamp, Location (longitude and latitude), RSRP (dBm), RSRQ (dB), SNR (dB), CQI (target), RSSI (dBm), and Downlink (DL) and Uplink (UL) bitrates (*Combine-All-the-Data-from-Lte-Dataset-into-One*, 2023).
LTE Combined Dataset consists of 102, 557 records and sixteen features that are Timestamp, Longitude, Latitude, Speed, Network Mode, RSRP, RSRQ, SNR, RSSI, DL and UL Bitrates, Serving Cell Information, and Path (transport mode)(*5G Dataset*, 2020).

### Data Preparation

Preprocessing of the data was done to make sure that it was of quality and fit that was necessary to machine learning. The duplicate records and missing values were eliminated. Domain specific filtering used selected the measurements that fell within reasonable RF ranges (see Table 1), trimming the aggregate data set by more than 31,000 records. Quantile-based procedures identified and eliminated the outliers to ensure that the model was not trained on extreme values.

Histograms and Q-Q plots to evaluate the distribution of features were part of the exploratory data analysis, and box plots were used to visualize and verify the removal of outliers (Kang & Tian, 2018; Moltchanov, 2019)

*Table 1: RSRP, RSRQ and SNR values standard range*

| **RSRP (dBm)** | **RSRQ (dB)** | **SNR (dB)** | **CQI** |
|---|---|---|---|
| ≥ -80 | ≥ -10 | ≥ 20 | 15 |
| -90 to -80 | -15 to -10 | 13 to < 20 | 12 - 14 |
| -100 to -90 | -20 to -15 | 0 to < 13 | 5 - 11 |
| < -100 | < -20 | ≤ 0 | ≤ 4 |

The characteristics with a substantial correlation with CQI were prioritized to be incorporated into the modeling procedure to make sure that the analysis uses the most significant predictors (Denis, 2021).

Such pretreatment ensured that the data was clean and comparable across all instances and acceptable in terms of modeling. The data were thoroughly prepared through the usage of powerful statistical tools and the knowledge of the field in order to develop accurate and reliable models of prediction of CQI. Data protection in machine learning is the core aspect because it directly influences the extent to which the model can learn on the data and give realistic predictions(Kang & Tian, 2018).

**Machine Learning Models**

Three baseline models were chosen, Linear Regression (LR), Gradient Boosting Regressor (GBR) and Feed-forward Neural Network (FNN), to compare CQI prediction on a variety of learning paradigms. It was specifically these models that were selected since they form a set of complementary classes of hypothesis, all capable of explaining different aspects of the behavior of LTE signals. Given that CQI values were 1-15, the initial inspection revealed that various models can yield more predictable results within various CQI sub-ranges, implying that the integration of both could give more predictable results across the entire range.

Linear Regression offers an easily understandable base-line and works well in cases where the correlation between radio-signal indicators and CQI is roughly linear. Although was less effective in the models of non-linear variations of channels, whereas LR sets a baseline against which better models can be evaluated (Su et al., 2012).

Gradient Boosting Regressor was chosen because it can be used in modeling non-linear patterns with sequential tree boosting. GBR eliminates residual errors progressively and has been very effective in wireless prediction problems where the relationships between RSRP, RSRQ, RSSI and SNR are non-linear (Natekin & Knoll, 2013).

Feedforward Neural Network represents complex interactions of features with many hidden layers. FNN in contrast to LR and tree-based methods learns hierarchical relation-ships hence being appropriate in areas where channel behavior changes fast. This array of learning behavior inspired the move towards ensemble approach. (*Effiecient Learning Machines*, 2017.; *Ensemble Learning in Machine Learning: Stacking, Bagging and Boosting*, 2023; Wolpert, 1992).

**Stacking Ensemble**

A stacking ensemble was created to enhance the strength and combine the strengths of single models. LR, GBR, and FNN are used as base learners and another FNN is used as a meta-learner. The selection of this architecture was made on two notes:

1. There were only specific CQI value ranges in which individual models gave reliable results.
2. Theoretical discrepancies in the generalization of errors by the models indicated that a combination of the models could fit a wider range of performance.

The piling process had a two-phase training process.

In Stage-1, the training was independently trained on each base learner on training set. Out of-fold (OOF) predictions were created in order to prevent information leakage with the help of k-fold cross-validation. These OOF predictions create a new intermediate feature space that is a reflection of the interpretation of the input by each model.

Stage-2: the stacked OOF output was used as input features to train the meta-learner (FNN). By training on learning to make generalizations between base model predictors as opposed to raw features, the meta-learner is able to learn optimum weighting and interaction relationships, leading to better generalization.

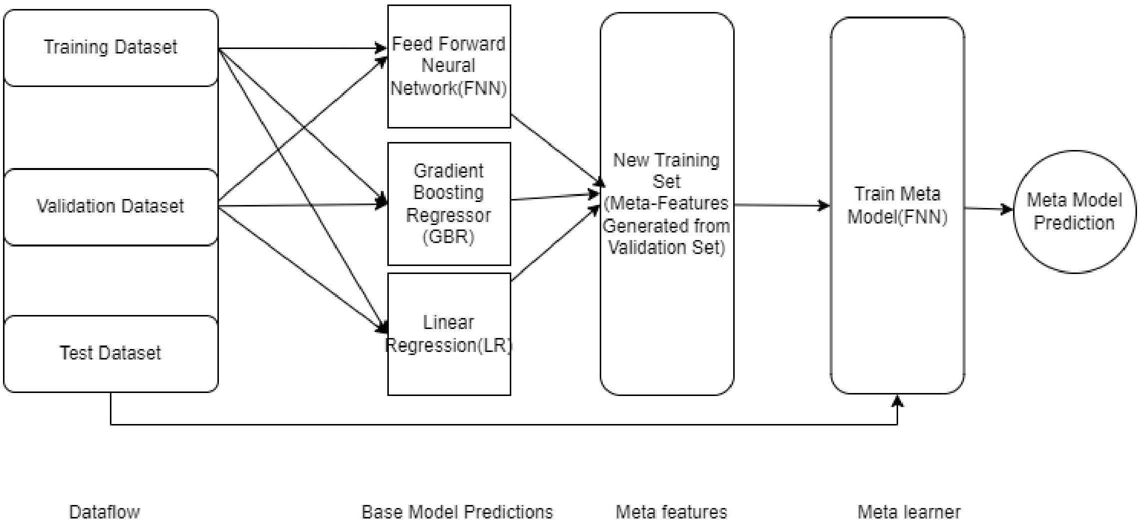


*Figure 2:* Proposed Stacking Model

**Data Splitting**

Table 2 reveals data splitting strategy. This study used 13, 268 LTE samples. In the case of training the base models, 80/20 split was implemented with 10,614 samples being used to train LR, GBR and FNN, and 2,654 samples being used to create out-of-fold predictions to use in the stacking process. The base models generated a prediction on each sample to give a meta-feature matrix of 2,654 by 3. This meta-dataset was again di-vided into 60 training, 20 validation and 20 test of the meta-learner (FNN) to provide unbiased learning and sound evaluation.

*Table 2: Dataset split used for baseline and stacking experiments*

| Experiment Stage | Train (%) | Validation (%) | Test (%) | Purpose |
|---|---|---|---|---|
| Base Model Evaluation | 80 | — | 20 | Benchmark performance |
| Stacking Ensemble | 60 | 20 | 20 | Meta-learner training + final evaluation |

### Hyperparameters tuning

Hyperparameters of model tuning are presented in Table 3. The grid search of the 5-fold cross-validation was applied to optimize the learning rate, depth, and the width of the layers. Weights of the neural networks were initialized with Glorot Uniform (seed=42) and trained with the Adam optimizer with MAE loss.

*Table 3: Hyperparameter settings for all learning models.*

| Model | Key Hyperparameters |
|---|---|
| Linear Regression | Polynomial degree=2 (via pipeline) |
| Gradient Boosting Regressor | n_estimators=200, learning_rate=0.05, max_depth=4, subsample=0.8 |
| FNN (Base Learner) | Layers: 64→32→1, activation=ReLU, epochs=100, batch_size=32 |
| FNN (Meta-Learner) | Layers: 64→32→1, activation=ReLU, optimizer=Adam, epochs=100 |

### Overfitting Prevention

A number of steps were undertaken to minimize overfitting. The FNN models included dropout layers and L2 regularization of dense layers. Validation loss was used to monitor meta-learner training and early stopping was used to avoid unjustified epochs. Splitting K-folds in the generation of meta-features also provided robust learning.

### Evaluation Metrics

A model performance was considered as a set of quantitative parameters and this considers both the predicted accuracy and the computational efficiency. Mean Absolute Error (MAE) and coefficient of determination ($R^2$) were used to measure prediction performance. MAE is calculated using the absolute differences between predicted and actual CQI values, and is used to form an indication of the average magnitude of the prediction errors. Lower values of MAE indicate more precise estimation and it is particularly effective in regression problems whose targets are discrete as in CQI. $R^2$ is the proportion of the change in the target variable that the model explains, which gives a more in-depth view of predictive fit.

In addition to accuracy, computational performance was assessed through training duration and prediction delay. The training period is the overall time necessary to fit a model to the training dataset, including preparation and parameter tuning. Prediction latency is the time it takes to develop CQI estimations for previously unseen data and is a critical concern for real-time or near-real-time LTE applications. These measures, when combined, allow for a comprehensive model comparison that balances accuracy with practical practicality(Willmott & Matsuura, 2005).

## Result and Discussion

The predictive models on estimating CQI were tested with both single algorithms LR, Ridge, Lasso, SVR, FNN, LSTM, and GRU and ensemble algorithms, such as Bagging Regressor, GBR and the suggested stacking ensemble. The measures of accuracy of the model were MAE and $R^2$, whereas the computational efficiency was determined as the memory consumption, training time and time to predict a sample.

*Table 4: Comparison of MAE and R-square of different algorithms*

| Model | MAE | R-Square |
|---|---|---|
| Linear Regression | 0.92 | 0.92 |
| Ridge Regression | 0.87 | 0.93 |
| Lasso Regression | 1.2 | 0.88 |
| LSTM | 0.74 | 0.91 |
| GRU | 0.72 | 0.91 |
| Feedforward Neural Network | 0.76 | 0.94 |
| Support Vector Regressor | 0.76 | 0.94 |
| Bagging Regressor | 0.77 | 0.89 |
| Gradient Boosting Regressor | 0.73 | 0.91 |
| Stacking (Proposed) | 0.66 | 0.93 |

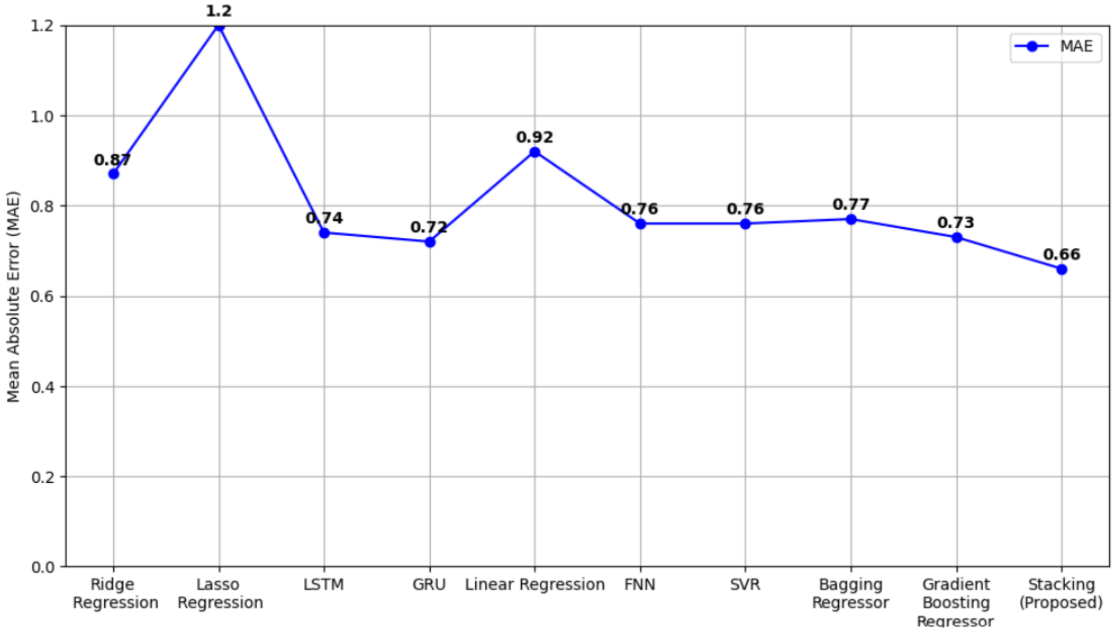


*Figure 3: Mean absolute error comparison of different machine learning algorithms.*

Table 2 provides an overview of the best predictive performance of the stacking ensemble as it has the lowest MAE (0.66) and high $R^2$ (0.93), which shows that the ensemble has better predictive performance. Base models that were used in the stacking ensemble (LR, GBR, and FNN) were selected based on their complementary strengths of capturing linear, non-linear, and complex interaction. The predicted CQI values (Table 3) are close to the actual values, especially in terms of mid to high range CQI. The lower CQI levels of 1-2 demonstrated more deviation, probably because of changing network conditions and data imbalance because there were less low CQI samples.

*Table 5: Actual and Predicted CQI of proposed meta model*

| Actual CQI | Avg. Predicted CQI (meta model) |
|---|---|
| 1 | 3.32 |
| 2 | 3.12 |
| 3 | 3.55 |
| 4 | 3.83 |
| 5 | 6.86 |
| 6 | 7.34 |
| 7 | 7.3 |
| 8 | 7.45 |

| Actual CQI | Avg. Predicted CQI (meta model) |
|---|---|
| 9 | 9.82 |
| 10 | 10.9 |
| 11 | 11.08 |
| 12 | 11.64 |
| 13 | 14.71 |
| 14 | 14.78 |
| 15 | 14.86 |

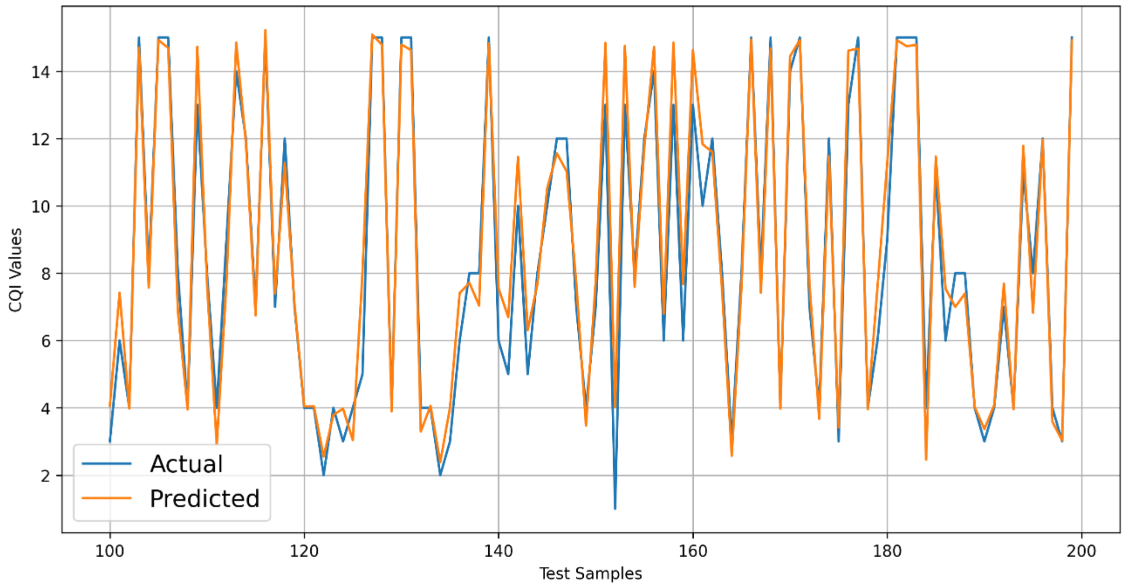


*Figure 4: Actual vs Predicted value of Proposed Stacking Model*

The stacking ensemble had a longer training time (64.3 s) and memory (0.43 MB) requirement than single models, but the prediction time (0.052 ms/sample/sample) was still viable in order to deploy the model in real-time (Table 4). Single models (LR and Ridge) were quicker to train but with greater MAE whereas GBR and FNN had superior accuracy with small computing expense. These findings indicate the trade-off between predictive accuracy and computational efficiency and affirm that the stacking method is an effective way to combine the bests of different models to provide effective CQI prediction in a wide range of network scenarios.

*Table 6: Performance Comparison of Regression, Neural and Ensemble Models*

| **Model** | **Memory Usage (MB)** | **Prediction time (ms/Sample)** | **Training Time (s)** | **Laptop specs** |
|---|---|---|---|---|
| Linear Regression | 0.02 | 0.00037 | 0.00228 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |
| Ridge Regression | 0.02 | 0.00029 | 0.00267 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |
| Lasso Regression | 0.02 | 0.00043 | 0.00277 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |
| LSTM | 0.41 | 0.13 | 9.6 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |
| GRU | 0.38 | 0.12 | 7.2 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |
| Feedforward Neural Network | 0.33 | 0.09 | 5.62 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |
| Support Vector Regressor | 0.04 | 0.031 | 0.48 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |
| Bagging Regressor | 0.048 | 0.019 | 0.48 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |
| Gradient Boosting Regressor | 0.02 | 0.0015 | 0.17 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |
| Stacking (Proposed) | 0.43 | 0.052 | 64.3 | 11th Gen Intel Core i5- 4 cores, 8GB RAM |

Altogether, the suggested stacking ensemble has great potentials in the practical LTE system implementation, offering adequate CQI estimation with reasonable computation needs. Low CQI predictions deviation hints at the future research paths, including the possibility of increasing the sample of low-CQI or attaching other context-related capabilities to the models to improve the reliability even more.

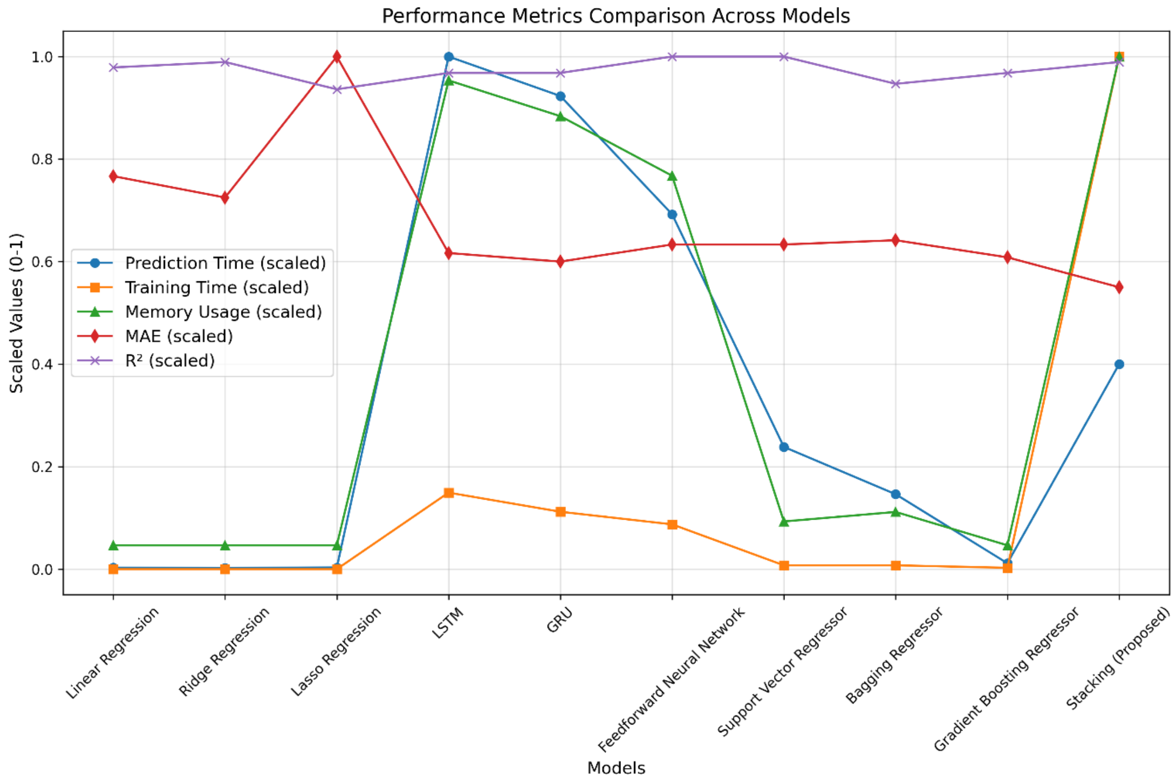


*Figure 5: Performance metrics comparison of different machine learning model*

**Training vs Validation Loss**

Figure 6 shows the training and validation curves of stacking ensemble model. As both curves approach each other with a smooth decline and converged without much variation, there is a stable process of learning the curves depict. This trend suggests that the ensemble has high generalization to novel data and achieves success in modeling the underlying associations of the LTE signal features. Additional indicators of weak overfit-ting are the absence of a large distance between the curves indicating that the meta-learner is successful in adopting the predictive capabilities of the base models. In general, the trends of training-validation confirm that the stacking framework provides a reliable and balanced learning behavior that suits CQI prediction activities.

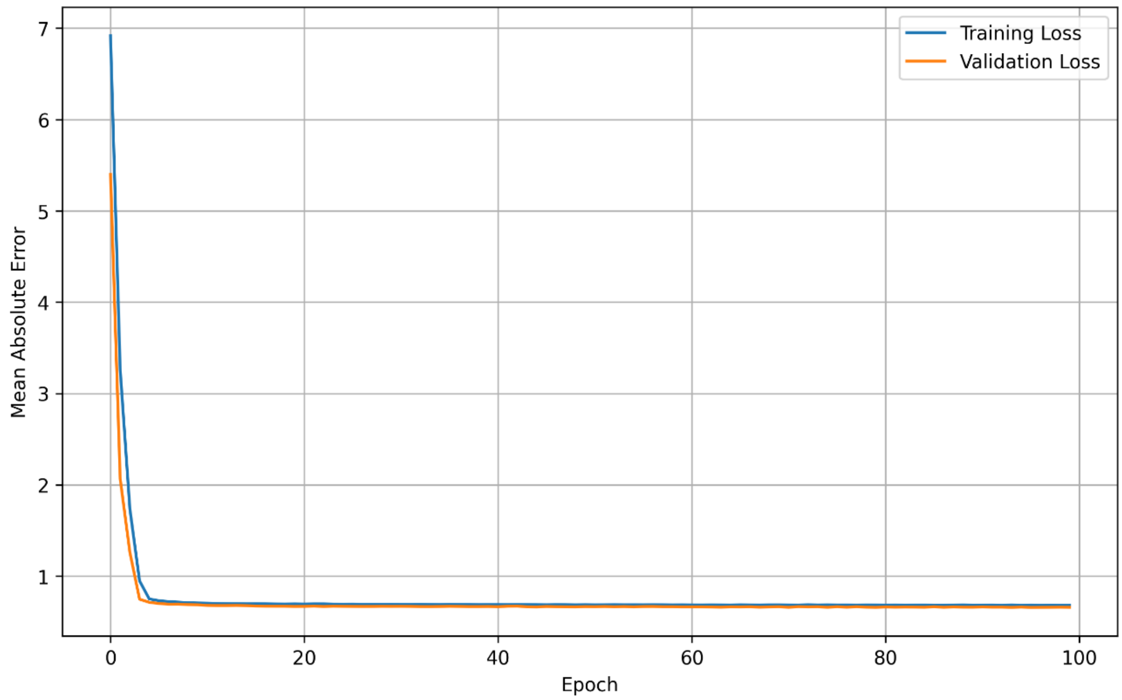


*Figure 6: Showing Validation Loss Vs Training Loss of Proposed Stacking Model*

**Conclusion**

This paper examined predictive modelling of the Channel Quality Indicator (CQI) in LTE networks, first individually with machine learning algorithms, and then in ensembles. The empirical findings prove that the suggested stacking ensemble, consisting of Linear Regression, Gradient Boosting Regressor, and Feedforward Neural Network as a base model together with an FNN meta-learner, is always more accurate and robust in its performance compared to a single model. The stacking model produced the least Mean Absolute Error (0.66), high R-squared (0.93) with realistic prediction times to be deployed in real-time.

The results indicate the benefits of ensemble methods when predicting CQI especially in handling of complex non-linear and linear associations among network attributes. Although the predictions of low CQI values were also more varied because of the imbalance between the datasets and the changing nature of the network conditions, the model still proved to be highly useful in the mid- to high-range CQI values.

Further improvements of low-CQI prediction deviations can be made in future work either by boosting the underrepresented samples or adding other context-sensitive features. Additional studies may also be done on deployment in live LTE systems to confirm real-time functionality and test adaptive functionality in dynamic network environments. Altogether, the suggested ensemble method offers a strong framework of precise and effective CQI prediction and enhances the process of distributing resources and optimizing networks in LTE settings.

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