Comparative Analysis for Doppler Shift Prediction in High-Speed 5G Scenarios

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***Abstract*— This study investigates the prediction of Doppler shift variations in high-speed rail (HSR) environments using advanced deep learning and classical time-series models. By simulating Doppler shifts at a 5G carrier frequency under noisy conditions, we evaluate and compare the performance of Bidirectional Long Short-Term Memory (LSTM) networks, Gated Recurrent Unit (GRU) networks, and an optimized Auto-Regressive Integrated Moving Average (ARIMA) model. The results highlight the strengths and limitations of each model, providing a detailed comparison between data-driven and statistical forecasting methods in dynamic 5G communication scenarios.**

Keywords—5G MIMO, Doppler Shift Prediction, Time-Series Forecasting, LSTM, GRU, ARIMA, Wireless Communication

I. Introduction

The rapid development of high-speed rail (HSR) networks, with trains operating at speeds exceeding 300 km/h, has introduced new challenges in wireless communications. Ensuring robust connectivity at such velocities is critical, particularly within the context of 5G networks, where Ultra-Reliable Low-Latency Communication (URLLC) is essential for passenger safety and efficient operation. A key obstacle in these high-mobility environments is the Doppler effect, which induces frequency shifts that degrade signal quality. In 5G systems, the impact of Doppler shifts is exacerbated by high carrier frequencies, often leading to signal fading, reduced data rates, and communication outages. As a result, accurate and timely prediction of Doppler shifts is vital for dynamically adjusting communication parameters and maintaining service reliability.

Traditional approaches like the Auto-Regressive Integrated Moving Average (ARIMA) model have been widely adopted in time-series forecasting due to their simplicity and interpretability. While ARIMA performs adequately for linear and stationary data, it struggles to model the non-linear, noisy patterns typical of Doppler shifts in HSR contexts [1], [2]. In contrast, deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are capable of capturing long-term dependencies and complex temporal patterns. Bidirectional architectures further enhance these models by leveraging both past and future contextual information [3]–[6]. Moreover, hybrid models like CNN-LSTM have demonstrated superior performance in Doppler shift forecasting for LTE and 5G networks by effectively modeling non-linear dynamics [7]–[9].

Despite these developments, the specific application of bidirectional LSTM and GRU models for Doppler shift prediction in high-speed rail scenarios remains relatively unexplored. This study addresses this research gap by conducting a thorough comparative analysis of Bidirectional LSTM, GRU, and ARIMA models. The evaluation includes performance under noisy conditions to better reflect real-world environments. Our findings offer practical insights into the trade-offs between traditional statistical and modern deep learning approaches, emphasizing their respective roles in enhancing 5G communications within high-mobility contexts.

The structure of this paper is as follows: Section II presents the mathematical analysis of the models, describing the key equations governing LSTM, GRU, and ARIMA networks. Section III provides an analysis of the algorithms, covering the role of dense layers, activation functions, and optimization techniques. Section IV details the testbed environment, outlining the simulation setup, parameter selection, and evaluation metrics. Section V presents the performance evaluation, comparing Bidirectional LSTM, GRU, and ARIMA models based on their accuracy using Mean Squared Error (MSE). Finally, Section VI discusses the findings, their implications, and potential future directions for improving Doppler shift prediction in high-speed 5G communication systems.

II. Mathematical Analysis

By preserving long-term dependencies via a sequence of specialized gates, LSTM networks are made to handle sequential data, as seen in Figure 1. The architecture consists of three primary components: the input gate, the forget gate, and the output gate. The input gate I_t decides which values from the input xt should be updated to the cell state Ct (1):

$$I\_t = \sigma(Wi \cdot [ht - 1, xt] + bi) \quad (1)$$

The information that should be removed from the cell state is decided by the forget gate ft (2):

$$ft = \sigma(Wf \cdot [ht - 1, xt] + bf) \quad (2)$$

The output gate ot regulates the output based on the input and the cell state (3):

$$ot = \sigma(Wo \cdot [ht - 1, xt] + bo) \quad (3)$$

The cell state Ct is updated using the input and forget gates, which allows the LSTM to retain or forget information as needed (4):

$$Ct = ft * Ct - 1 + it * tanh(Wc \cdot [ht - 1, xt] + bc) \quad (4)$$

And finally, the hidden state h_t is updated to produce the output (5) [10]:

$$ht = ot * tanh(Ct) \quad (5)$$

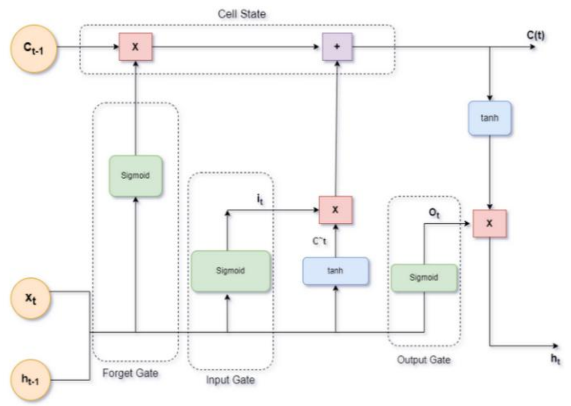

Fig. 1. Architecture of a LSTM unit

The GRU shares many similarities with the LSTM network, but with a simplified architecture which can be seen in Figure 2. As seen, LSTM networks have three gates—input, forget, and output—GRUs combine the functions of the forget and input gates into a single update gate. Additionally, GRUs use a reset gate to control how much of the past information is retained. This streamlined design makes GRUs computationally more efficient than LSTMs, as they require fewer parameters and thus less memory and processing power.

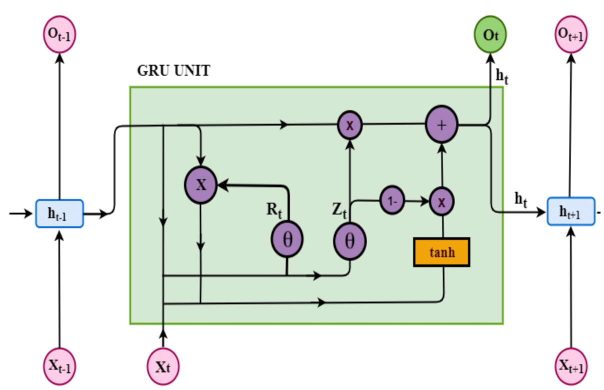

Fig. 2. Architecture of a GRU unit

In comparison to the LSTM network, the GRU can effectively capture dependencies in sequential data with a simpler structure according to the formulation shown in Figure 2. To create the new hidden state ht, the update gate zt determines how much of the candidate hidden state h~t and the prior hidden state ht−1 should be combined. (6):

$$zt = \sigma(Wz \cdot [ht - 1, xt] + bz) \quad (6)$$

When determining the candidate hidden state h~t, the reset gate rt determines how much of the previous hidden state should be forgotten. (7):

$$rt = \sigma(Wr \cdot [ht - 1, xt] + br) \quad (7)$$

The candidate hidden state h~t is computed by applying a non-linear transformation to the input xt and the reset version of the previous hidden state ht−1 (8):

$$h{\sim}t = tanh(Wh \cdot [rt \circ ht - 1, xt] + bh) \quad (8)$$

The final hidden state ht is then updated by combining the candidate hidden state h~t and the previous hidden state ht−1 as controlled by the update gate zt (9) [11]:

$$ht = (1 - zt) \circ ht - 1 + zt \circ h{\sim}t \quad (9)$$

The last model used (and compared to the other two) is one that is frequently used in time series forecasting problems such as this one. ARIMA, combines three components: Autoregression (AR), Integration (I), and Moving Average (MA). The AR part of the model represents the relationship between an observation and a specified number of lagged observations (i.e., previous time steps). The integration part I involves differencing the data to make it stationary, which is crucial because ARIMA assumes that the time series has a constant mean and variance over time.

Finally, the MA component uses a moving average model applied to delayed observations to represent the link between an observation and the remaining errors. Where p is the number of lag terms, d is the degree of differencing, and q is the number of lagged forecast errors in the prediction equation, the ARIMA model is generally expressed as ARIMA (p, d, q). ARIMA is particularly effective in capturing the linear trends and seasonality in the data, making it a valuable baseline model for time series analysis. The disadvantage of ARIMA however, is its limitation its ability to capture complex non-linear patterns [12].

III. Analysis of Algorithms

Dense Layers are typically employed towards the end of a neural network to transform the feature representations into the desired output format, such as classification logits or regression outputs. The dense layer performs a linear transformation followed by an activation function. The formula for a dense layer is y=f(Wx+b), where x is the input vector, W represents the weight matrix, b represents the bias vector, and f is the activation function applied individually for each element.

Signal preprocessing is a critical step in preparing Doppler shift data for time series modeling. Initially, the Doppler shifts are normalized using a MinMaxScaler to ensure that the values lie within a consistent range, typically between 0 and 1. This step is crucial because many machine learning algorithms, including LSTM and GRU networks, perform better with normalized input data [13]. After normalization, the stationarity of the series is checked using the Augmented Dickey-Fuller (ADF) test. If the series is found to be non-stationary, which means it has trends or varying mean over time, differencing is applied. Differencing is a technique that subtracts the current value from the previous value, effectively stabilizing the mean of the series [14], [15]. This processed data is then ready for training predictive models.

Algorithm – Stationarity check and normalization

```
function preprocess_signal(doppler_shifts, adf_test_threshold=0.05):
    initialize MinMaxScaler
    # Normalize Doppler shifts
    normalized_shifts = MinMaxScaler.fit_transform(doppler_shifts)
    # Check for stationarity using Augmented Dickey-Fuller (ADF) test
    adf_result = perform_adfuller_test(normalized_shifts)
    if adf_result.p_value > adf_test_threshold:
        # Apply differencing to stabilize the series
        differenced_shifts = difference(normalized_shifts)
    else:
        differenced_shifts = normalized_shifts
    return differenced_shifts
```

The plot in Figure 3 illustrates the noisy and normalized Doppler shifts experienced in a high-speed (such as that of trains) over a period. Noise was added to simulate real-world conditions. The underlying doppler shift (the "clean" one) is the one our models will try to predict. The Doppler shifts vary continuously, reflecting the dynamic nature of the high-speed movement and the environmental factors affecting the signal. The normalization ensures that the values are scaled, making it easier to observe the relative fluctuations in Doppler shift intensity. The presence of noise introduces variability, mimicking the unpredictable changes in signal frequency that occur in practical scenarios, such as due to obstacles, weather, or other interference sources. This noisy Doppler shift data serves as a challenging test case for predictive models aimed at enhancing signal strength by compensating for such shifts.

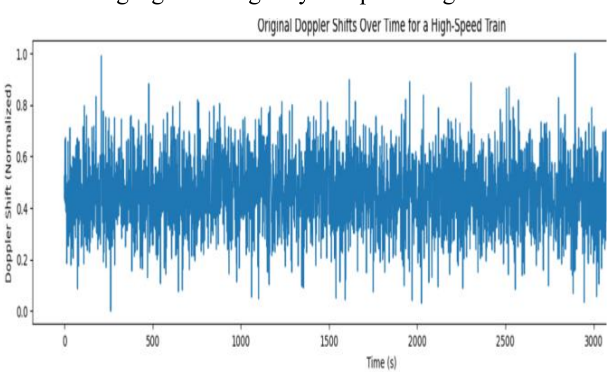

Fig. 3. Noisy Doppler Shift Over Time (Normalized)

The LSTM and GRU models used in this study are designed to capture the temporal dependencies in Doppler shift time series data. Both models employ a Bidirectional architecture, which allows them to learn from both past and future context within the sequence, enhancing their predictive power for time-dependent data.

In the LSTM model, three layers of Bidirectional LSTM units are employed, each followed by a LeakyReLU activation function, LayerNormalization, and Dropout [16]. The LeakyReLU activation function allows a slight gradient when the unit is not in use, which helps to alleviate the vanishing gradient problem. LayerNormalization stabilizes the learning process by normalizing the output of each layer, while Dropout is used to prevent overfitting by randomly disabling a fraction of neurons during training.

Similarly, the GRU model follows the same architecture but with GRU units. GRUs are computationally more efficient than LSTMs due to their simpler structure, making them suitable for tasks where faster training is beneficial. The choice of Bidirectional layers in both models allows the networks to access context from both directions, which is particularly useful for time series data where future events can influence past ones. The two models have a similar structure. The structure of the LSTM model is shown in the "build_lstm_model" function below.

Algorithm – LSTM and GRU structure

```
function build_lstm_model(seq_length):
    model = Sequential()
    # First Bidirectional LSTM Layer
    model.add(Bidirectional(LSTM(units=256, return_sequences=True, input_shape=(seq_length, 1))))
    model.add(LeakyReLU(alpha=0.01))
    model.add(LayerNormalization())
    model.add(Dropout(0.3))
    # Second Bidirectional LSTM Layer
    model.add(Bidirectional(LSTM(units=128, return_sequences=True)))
    model.add(LeakyReLU(alpha=0.01))
    model.add(LayerNormalization())
    model.add(Dropout(0.2))
    # Third Bidirectional LSTM Layer
    model.add(Bidirectional(LSTM(units=64, return_sequences=True)))
    model.add(LeakyReLU(alpha=0.01))
    model.add(Dropout(0.1))
    # Output Layer
    model.add(Dense(units=1))
    return model
```

The optimizer for both LSTM and GRU based models was RMSProp, because it is particularly effective for handling non-stationary objectives and adaptive learning rates. Given the complexity and variability of predicting Doppler shifts in a dynamic environment, RMSprop helps maintain a stable and efficient learning process by adjusting the learning rate based on the average of recent squared gradients. This allows the model to converge more quickly and accurately by mitigating the risk of large updates that could destabilize the learning process, especially when dealing with sequences of data with varying patterns like Doppler shifts. The metric the model was compiled on was the MSE and several techniques such as "EarlyStopping" and "ReduceLROnPlateau" were used to ensure optimal training and monitoring on the loss and accuracy variables.

The ARIMA model chosen is the Auto-ARIMA in which the "Auto" refers to the automatic selection of the best ARIMA parameters, which include the order of the AR,I and MA components. This automatic selection process simplifies the model-building task by testing various combinations of these parameters and selecting the one that minimizes the error. By using the auto_arima function, the model automatically identifies the optimal parameters, ensuring the best fit for the given Doppler shift data.to differentiate between real signals and pure noise.

Algorithm- Auto-ARIMA model

```
function build_auto_arima_model(train_data):
    # Automatically select the best ARIMA model
    model = auto_arima(train_data, seasonal=False, stepwise=True, suppress_warnings=True)
    return model

function predict_with_arima_model(model, steps):
    # Generate forecast using the selected ARIMA model
    forecast = model.predict(n_periods=steps)
    return forecast
```

IV. DESCRIPTION OF TESTBED

The simulation setup can be seen below, in Table I. It simulates Doppler shifts experienced by a high-speed train due to the Doppler effect in a 5G communication system. The simulation involves generating time series data for Doppler shifts based on a train traveling at a high speed. The testbed evaluates three different forecasting models: ARIMA, LSTM, and GRU, to predict Doppler shifts over time. The models are compared based on their RMSE and complexity.

TABLE I. SIMULATION PARAMETERS

Parameter	***Value***
Carrier Frequency	3.5 x 10^9
Total Simulation Time	3600
Time per Step (s)	1
Cosine Factor	Π/4
LSTM Units	128
LSTM Activation Function	ReLU
GRU Units	128
GRU Activation Function	ReLU
More Layers Used	Dense
ARIMA Parameter P	1
ARIMA Parameter D	1
ARIMA Parameter Q	3
Evaluation Metrics	RMSE

In the context of Long LSTM networks, the Rectified Linear Unit (ReLU) activation function offers an alternative to the traditionally used sigmoid and tanh functions. ReLU, defined as ReLU(x)=max(0,x), introduces non-linearity into the model by allowing only positive values to pass through, effectively setting all negative values to zero. While LSTMs primarily utilize sigmoid and tanh functions for their gating mechanisms and cell state regulation, incorporating ReLU in the hidden layers of LSTMs can potentially enhance their performance. The primary advantage of using ReLU is its ability to introduce sparsity in activations, which can lead to more efficient learning and reduced overfitting. Additionally, ReLU helps address the vanishing gradient problem, allowing gradients to propagate more effectively through the network. In many neural network topologies, dense units, also known as fully connected layers, are a fundamental component. Each neuron in these levels is coupled to every other neuron in the layer above it. This dense connectivity allows the model to learn complex representations of the data.

V. PERFORMANCE EVALUATION

In this section, we present a detailed analysis of the performance of LSTM, GRU, and ARIMA models in predicting Doppler shifts in HSR communication systems. The predictions made by each model are compared to the actual Doppler shift values over time, highlighting the strengths and limitations of each approach. Specifically, we examine how the models handle complex, non-linear patterns in Doppler shift data and evaluate their accuracy through MSE.

As shown in Figure 4, both the LSTM and GRU models provide predictions that closely follow the actual Doppler shift values as time passes, with the GRU model demonstrating slightly better results. The LSTM model shows that it can also converge to an optimal solution as time passes. But, while the LSTM is effective, its more complex architecture may occasionally struggle with fine-tuning predictions in the presence of intricate patterns or smaller datasets.

In contrast, the GRU model, with its simplified and more streamlined architecture, manages to maintain high accuracy throughout the entire time series. By merging the input and forget gates into a single update gate and incorporating a reset mechanism, this model efficiently captures temporal dependencies while reducing architectural complexity. As a result, the GRU is particularly adept at modeling the non-linear patterns evident in the Doppler shift data, which is crucial for accurately predicting shifts in dynamic environments. The GRU's ability to adapt quickly when the dataset is not very big, highlights its robustness, especially in scenarios where computational efficiency and real-time adaptability are critical.

The superior performance of the GRU model is quantitatively reflected in its MSE, which was the lowest among all the models tested. Specifically, the GRU model began with a starting MSE of 0.65, but as time progressed and the model continued to refine its predictions, it achieved an impressively low MSE of 0.04. This significant reduction in error underscores the GRU's strong learning capacity and its ability to fine-tune predictions with continued exposure to data compared to the ARIMA.

In comparison, the LSTM model also demonstrated commendable performance, ending with a final MSE of 0.05. However, the slightly higher error relative to the GRU suggests that the LSTM may be more susceptible to overfitting. These observations are further detailed in Table I, which summarizes the average offsets over various steps

Overall, the GRU's superior forecast capability of the actual Doppler shifts, as seen in Figure 4, suggests that its architecture not only offers computational advantages but also enhances predictive accuracy in environments where maintaining real-time, reliable predictions with little data is essential. These results indicate that the GRU's efficiency in handling sequential dependencies, combined with its resilience against overfitting, may give it a distinct edge in predictive tasks, where we have a small dataset and do not need the extra complexity in the neural network's layers.

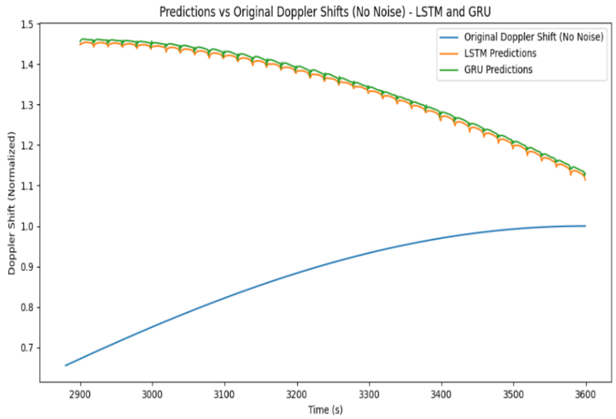

Fig. 4. Forecast of the LSTM and GRU models

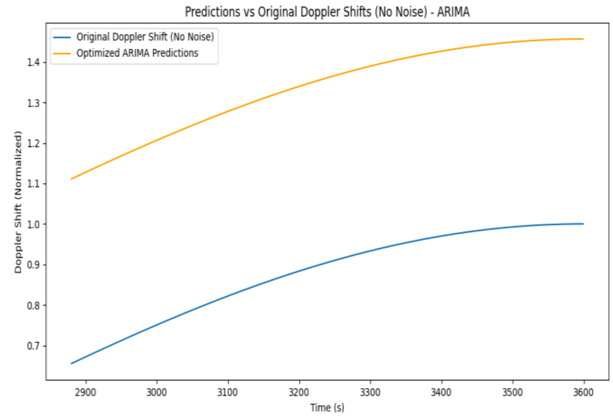

Fig. 5. Forecast of the ARIMA models

TABLE I. OFFSET SCORES OF LSTM/GRU MODELS

Testing Steps	*Average Offset*
100	0.22413
250	0.21231
500	0.20193
1000	0.21034

Figure 5 illustrates the performance of the ARIMA model in predicting the Doppler shifts. The ARIMA model effectively models linear trends but is inherently limited by its reliance on fixed lag structures and linear assumptions. Doppler shifts in HSR scenarios are characterized by complex non-linear patterns influenced by environmental factors and rapid mobility, which the ARIMA model cannot adapt to. This limitation becomes evident in its inability to track abrupt changes or fluctuations, as shown by its high Mean Squared Error (MSE) of 0.2, the highest among the tested models.

While the ARIMA model provides a good starting estimation, it fails to adapt to the trends in the data. This is expected due to its reliance on linear relationships and its limitation in handling non-linear patterns. These results suggest that while ARIMA might offer a quick and computationally inexpensive solution for trend estimation, its inability to model non-linear behaviors makes it less suited for real-time Doppler shift adjustments in 5G systems.

In contrast, deep learning models like GRU and LSTM excel in these scenarios due to their ability to capture complex temporal dependencies, as evidenced by their significantly lower MSE scores. Table II shows the average offset after multiple runs, which, along with Table I, further emphasizes the superior performance of the neural network-based models over the ARIMA model in accurately predicting Doppler shifts.

TABLE II. OFFSET SCORES OF ARIMA MODEL

Runs	*Average Offset*
100	1.43412
250	1.43412
500	1.43412
1000	1.43412

So, as was observed, the GRU model outperformed both the LSTM and ARIMA models in predicting Doppler shifts, as indicated by its lower MSE. The LSTM model, while slightly less accurate than the GRU, still performed well and demonstrated its strength in handling complex sequential data. The ARIMA model, while useful for capturing general trends, was less effective in modeling the nuanced, non-linear patterns inherent in the Doppler shift data. These results underscore the advantage of using deep learning models, particularly GRU and LSTM, for predicting Doppler shifts in HSR communication systems, where the ability to capture intricate temporal dependencies is crucial.

Given a GRU's best MSE of 0.04, LSTM's best MSE of 0.05, the forecasted MSE of the ARIMA model of 0.2, we can deduct that predicting the shifts with an LSTM-based or GRU-based neural network can have a significant impact in enhancing the performance of 5G networks, particularly in high-mobility scenarios. This impact can be observed in multiple sections of a 5G communication.

Firstly, by reducing MSE in Doppler shift estimation, our model enables more precise Channel State Information (CSI) acquisition, leading to significant improvements in Adaptive Modulation and Coding (AMC) schemes. Specifically, the achievable data rate R can be modeled as :

$$R = B \cdot log2(1 + (abs(H))\hat{}2 \; / \; N0 + I * P) \tag{10}$$

where B is the bandwidth, P is the transmitted power, the absolute value of H (squared) represents the channel gain, N0 is the noise power, and I is the interference. Our Doppler prediction minimizes errors, optimizing the AMC performance.

Moreover, accurate Doppler estimates can enhance beamforming accuracy in mmWave communications, modeled by the beamforming gain modeled as :

$$G = 4\pi d\lambda \cdot cos(\theta - \theta d) \tag{11}$$

where λ is the wavelength, d is the distance, θ is the angle of arrival, and θd is the desired beam direction. By reducing the angular deviation due to Doppler shifts, our model improves beamforming alignment, leading to higher signal strength and reduced outage probability. These advancements translate into measurable gains in throughput, reduced latency, and increased energy efficiency, making our model a valuable asset for enhancing 5G network performance.

Finally, another way that a very accurate Doppler shift prediction can enhance 5G communications is in the handovers. With accurate Doppler predictions, we can have more successful handovers and reduced handover failures. This improvement is crucial for maintaining continuous connectivity and high-quality service in 5G, thereby reducing latency, minimizing packet loss, and ensuring consistent user experience even at high speeds. Additionally, this enhanced handover performance can also contribute to network energy efficiency, as fewer resources are wasted on managing failed handovers, further solidifying the importance of Doppler shift prediction in the effective operation of 5G networks.

VI. Conclusion and Future Work

This paper presented a comparative evaluation of Bidirectional LSTM, GRU, and ARIMA models for predicting Doppler shifts in high-speed rail communication environments. The results clearly demonstrate the superior performance of deep learning models—particularly the GRU—in terms of accuracy and adaptability under dynamic and noisy conditions. These findings underscore the potential of integrating GRU and LSTM models into real-time 5G network protocols to improve communication reliability in high-mobility scenarios.

The success of these models invites several promising research directions. Future work may explore their integration into adaptive communication protocols, enabling real-time Doppler compensation in 5G systems. Additionally, combining these models with other advanced technologies, such as beamforming and MIMO, could further enhance communication robustness. Expanding the study to include other mobility scenarios, such as vehicular or drone-based networks, would also provide valuable insights into the generalizability of these predictive frameworks.

In conclusion, accurate Doppler shift prediction using deep learning models can play a pivotal role in ensuring seamless and efficient communication in the next generation of mobile networks. Their incorporation into 5G infrastructure represents a critical advancement toward achieving reliable connectivity in fast-evolving wireless environments.

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