response to rapid changes, with predicted values remaining marginally higher than actual ones. Finally, Figure 3d illustrates predictions for 24 samples (n_samples), where predicted values fall slightly below actual values, exhibiting the most significant lag while still capturing major trends in the data. Despite variations in prediction samples, all configurations effectively follow the overall pattern of soil moisture fluctuations, particularly during stable periods.

Figure 4 presents a scatter plot comparing actual values (x-axis) to predicted values (y-axis) across different prediction samples (6, 12, 18, and 24). The analysis reveals that the 12-sample model achieves the highest accuracy and consistency, with data points clustering closely around the ideal prediction line and minimal deviation. In contrast, the 6-sample model captures the overall trend but exhibits the widest spread and highest error, making it the least accurate of the four models. The 18-sample model performs well but shows minor errors at higher soil moisture levels, slightly diminishing its accuracy. The 24-sample model maintains a good fit but demonstrates increased variance at higher value ranges, indicating a slight drop in precision with longer prediction intervals. Overall, the 12-sample model stands out as the most reliable for soil moisture prediction, offering an optimal balance between accuracy and interval length.

TABLE I. ExperimentSummary

| Number of Samples (n_samples | Measurement | | | |
|---|---|---|---|---|
| | ***RMSE*** | ***MAE*** | ***MAPE*** | ***R2*** |
| 6 | 0.66378 | 0.53720 | 0.04753 | 0.79305 |
| 12 | 0.46281 | 0.36648 | 0.03201 | 0.89944 |
| 18 | 0.53350 | 0.43273 | 0.03838 | 0.86652 |
| 24 | 0.50695 | 0.39835 | 0.03431 | 0.87955 |

To further evaluate the effectiveness of the GRU model across different configurations, Table 1 presents a comparison of prediction results from the GRU method. The performance metrics used include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and coefficient of determination ($R^2$). These metrics collectively indicate that n_samples =12 is the most effective sample size for prediction, yielding the lowest error rates (MAPE, RMSE, MAE) and the highest $R^2$ value. This sample likely represents an optimal balance where the GRU model can predict accurately without significant error magnitudes that can arise from either longer or shorter sample intervals.

## IV. CONCLUSION

This study demonstrates the effectiveness of utilizing Gated Recurrent Units (GRU) to predict soil moisture levels based on environmental data collected through IoT devices. By combining soil moisture data with temperature and humidity levels, the GRU model can deliver accurate short-term predictions, crucial for enhancing irrigation efficiency. Among various prediction intervals (6, 12, 18, and 24 samples), the 12-sample model consistently achieves the highest accuracy and reliability, striking an optimal balance between precision and responsiveness. Comparative analysis through performance metrics, including RMSE, MAE, MAPE, and $R^2$, confirms that the 12-sample model minimizes error rates while maximizing prediction quality. These findings underscore the potential of GRU-based models for real-time soil moisture monitoring, highlighting their significance in sustainable agriculture and smart farming applications.

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