average, predictions differ by only a small percentage from actual values. The low MAPE values support the ability of the model to provide accurate predictions. The R2 values are consistently high, with highest value (0.8970) achieved at n = 12, shows that the model explains approximately 89.7% of the variance in soil moisture values.

In terms of economic feasibility, cost-benefit analysis was performed in this research. The results show that the CBR value ranges from 526.67 to 1,085.71. In this case, the value show that the system is highly beneficial and offers a substantial return on investment. This demonstrates the economic feasibility of implementing proposed system, as it provides a significant financial return by reducing water and fertilizer costs.

IV. CONCLUSION

This research demonstrates that the LSTM model effectively predicts soil moisture values using time series data from IoT device. The model's performance, evaluated across different sample sizes (n = 6, 12, 18, and 24), consistently exhibits high accuracy and reliability. Graphs, scatter plots and accuracy metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R2) confirm the model's predictive capability.

The lowest RMSE and the highest R2 values were observed at n = 12, highlighting this step size as optimal, with a prediction accuracy of approximately 89.7% in explaining the soil moisture variance. Furthermore, the model maintained a low MAPE (around 3%) across all sample sizes, shows only minor deviations from actual values. The time series graphs further illustrate this by close alignment between the predicted and actual values, with minimal lag and smooth transitions that follow the actual data's fluctuations. The consistent clustering of points around the ideal prediction line in scatter plots further supports the robustness of the LSTM model in capturing temporal pattern within soil moisture data. Future work will focus on evaluating the generalizability of the model across diverse datasets and improving the system with user interface and data visualization tools to better align with the needs of farmers and agricultural experts.

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