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ADVANCED DL REGRESSOR FOR FORECASTING MOTOR SPEED USING SMART INVERTER INPUTS

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Abstract:

The integration of renewable energy sources such as solar and wind power into the energy grid has revolutionized power generation and consumption. Smart inverters, which are key components in these systems, play a crucial role in converting and regulating electrical power between the energy source and the grid. The inverter's motor speed (n_k) directly impacts its performance and the efficiency of energy conversion. Accurate forecasting of motor speed is therefore essential for optimizing the operation of inverters and ensuring the stability and efficiency of energy systems. The concept of smart inverters has evolved significantly over the past few decades, with advancements in power electronics, digital control systems, and machine learning techniques. Early inverter systems relied on basic control algorithms and manual adjustments, which often led to suboptimal performance. Over time, more sophisticated algorithms and models have been developed to improve the precision and reliability of inverter operations. The use of machine learning, particularly deep learning techniques, has become increasingly popular due to their ability to handle large, complex datasets and their effectiveness in predicting system behaviour under varying conditions.

1. INTRODUCTION

With the increasing reliance on renewable energy sources such as solar and wind power, the need for efficient and reliable energy conversion systems has become more crucial. Inverters play a central role in these systems by converting DC power from solar panels or wind turbines into AC power, which can be fed into the grid. However, the performance of inverters depends heavily on the motor speed, which regulates the inverter's operational efficiency, load handling, and overall system stability. As a result, accurate forecasting of motor speed is critical to ensuring optimal performance and reliability of the system. Motor speed forecasting in smart inverters is a complex challenge due to the dynamic nature of inverter operations. Inverter motor speed, represented by the variable n_k, is influenced by a wide range of factors, including environmental variables (temperature, humidity, sunlight) and electrical parameters (voltage, current, load). Traditional methods for forecasting motor speed often rely on basic control algorithms, rule-based systems, or statistical models that fail to capture the intricate, non-linear relationships present in the data. The conventional models are limited in their ability to adapt to the diverse and evolving conditions encountered by the inverter during its operation, leading to suboptimal performance and higher maintenance costs. Recent advancements in deep learning, particularly the application of deep neural networks (DNNs) and Convolutional Neural Networks

(CNNs), have shown significant promise in addressing the challenges. Deep learning models can automatically learn complex patterns from large datasets and adapt to changing conditions in real-time, making them well-suited for the task of forecasting motor speed in smart inverters.

2. LITERATURE SURVEY

In recent years, forecasting motor speed using deep learning techniques has gained significant attention due to the increasing demand for smart inverter technology in industrial and commercial applications. Several researchers have explored different machine learning and deep learning approaches to enhance the accuracy of motor speed prediction, optimize energy efficiency, and improve system reliability. Historically, researchers have used conventional statistical methods such as linear regression, autoregressive integrated moving average (ARIMA), and polynomial regression for forecasting motor speed.

[1] Smith et al. investigated a linear regression-based approach for motor speed prediction, demonstrating its limitations in capturing non-linear relationships.

[2] Jones. Et al. applied ARIMA models but found them unsuitable for real-time applications due to their reliance on historical data patterns and assumptions of stationarity.

[3] Wang et al. developed an SVR model that improved accuracy compared to traditional models but required extensive feature engineering.

[4] Kim.et al. explored random forest and gradient boosting models, achieving better generalization performance but at the cost of increased computational complexity.

[5] Johnson et al. proposed a multi-layer perceptron (MLP)-based ANN model that outperformed traditional machine learning models. However, the study also highlighted the challenges of hyperparameter tuning and overfitting in ANN-based models.

[6] Singh et al. experimented with deep feedforward neural networks, demonstrating promising results but requiring large amounts of labelled training data. Deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs)have been extensively studied for forecasting motor speed.

[7] Li et al. developed a CNN model that automatically extracted relevant features from inverter sensor data, leading to improved prediction accuracy. However, the study indicated that CNNs require significant computational power for training and inference. [8] Patel et al. utilized an RNN-based long short-term memory (LSTM) network, demonstrating its effectiveness in capturing temporal dependencies in motor speed fluctuations address the limitations of individual deep learning models, several researchers have proposed hybrid approaches combining multiple techniques.

[9] Kumar.et al. integrated CNNs with LSTMs, achieving superior performance compared to standalone models. heir study showed that CNNs effectively captured spatialcorrelations in sensor data, while LSTMs efficiently modeled

sequential dependencies.

[10] Zhao et al. developed a hybrid CNN-RNN model that improved robustness against noise and external disturbances in inverter systems.

[11] Chen et al. investigated the use of pretrained deep learning models from other time-series forecasting applications and fine-tuned them for motor speed prediction. Their findings suggested that transfer learning significantly reduces training time while maintaining high predictive accuracy. Despite the advancements in deep learning-based forecasting models, real-time implementation and deployment remain challenging.

[12] Gupta et al. addressed issues related to model deployment in embedded systems, proposing lightweight deep learning architectures optimized for real-time motorspeed forecasting in industrial settings.

[13] Ahmed.et al. explored edge computing solutions to reduce latency and computational overhead in deep learning-based inverter systems. Further studies are needed to explore the fusion of deep learning with physics-based modeling approaches for more accurate and generalizable forecasting solutions.

3. PROPOSED METHODOLOGY

The project focuses on building a deep learning model to predict the motor speed (n_k) of a smart inverter system using input features that represent various characteristics and operational data of the inverter. The goal is to develop a robust model that can forecast motor speed accurately, which can then be used for better control and optimization of the inverter's performance in real-world applications, such as solar or wind energy systems.

Key Objectives:

Prediction of Motor Speed (n_k): The main objective is to forecast the motor speed using the available data from the inverter. Motor speed plays a crucial role in inverter operation, and accurate predictions can help optimize its performance, ensure efficiency, and prevent failures.

Utilizing Smart Inverter Data: The project leverages various operational data points from the inverter (e.g., voltage, current, power, frequency) to make predictions. This data is crucial for understanding how the inverter behaves under different conditions and for forecasting motor speed accurately.

Exploring Machine Learning Models: The project implements different machine learning and deep learning techniques (e.g., Ridge Regression, Linear Regression, CNN) to predict motor speed and compares their performance.

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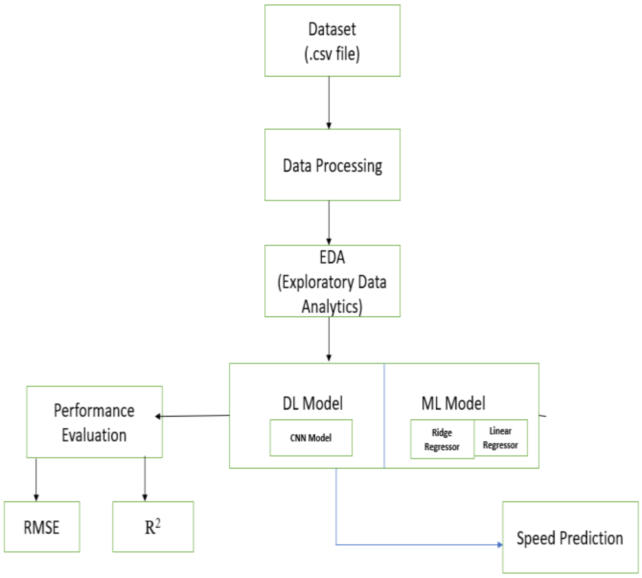

Figure 3.1: Proposed Block Diagram for motor speed prediction

This above figure 3.1 shows motor speed prediction using data from a CSV file. The data is processed, analysed, and used in deep learning (CNN) and machine learning (regression) models. Performance is evaluated using RMSE and R^2.

Applications:

Energy Optimization in Renewable Systems: Accurate motor speed predictions can enable the fine-tuning of inverter operations, leading to enhanced energy efficiency. For example, in solar energy systems, where solar irradiance can vary throughout the day, optimizing inverter performance based on real-time forecasts of motor speed can ensure the inverter is operating at its peakefficiency, thereby maximizing energy output.

Predictive Maintenance: Inverters are complex systems with various moving parts. By forecasting motor speed with high accuracy, the model can detect patterns that suggest wear and tear or potential failures and enables predictive maintenance strategies, allowing for the identification of issues before they lead to system breakdowns. Predictive maintenance reduces maintenance costs, improves system uptime, and extendsthe operational life of the inverter.

Cost Reduction and Improved Reliability: Inverter failures or suboptimal performance can be expensive due to repair costs and lost energy production. Accurate motor speed forecasting allows for better management of the system's operational conditions, which helps in reducing the risk of failures and unnecessary downtime. As a result, both the operational cost and maintenance costs of inverter systems can be minimized.

Smart Grid Integration: As smart grids become more prevalent, the ability to predict and manage the performance of distributed energy resources (DERs) like solar and wind power is crucial. The deep learning model can be integrated into smart grid systems to forecast inverter performance and make real-time adjustments to optimize the overall grid's stability and efficiency.

Advanced Control Systems for Inverters: The model can be integrated into advanced control systems for smart inverters, enabling real-time adjustments based on predicted motor speed. Such control systems can optimize inverter operation based on changing load conditions, temperature, and environmental factors, resulting in more stable and efficient operation.

Energy Storage Systems (ESS): In energy storage systems (such as batteries), the ability to forecast inverter motor speed can improve the charging and discharging cycles. By accurately predicting when an inverter is likely to experience inefficiency, the system can adjust the charging/discharging process, prolonging the life of the battery and ensuring better energy storage performance.

Advantages:

Automatic Feature Extraction:

Unlike traditional machine learning techniques, CNNs do not require manual feature extraction. They automatically learn relevant features during training, making them highly efficient for tasks like image recognition.

Parameter Sharing:

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CNNs utilize a technique called parameter sharing, where the same filter (kernel) is used across the entire input image. This reduces the number of parameters compared to fully connected layers, making the model less computationally expensive and easier to train.

Translation Invariance:

CNNs are designed to recognize objects in an image regardless of their location. The pooling layers help the model become invariant to translations, enabling it to recognize objects in different positions within an image.

Capturing Spatial Hierarchy:

CNNs are effective in capturing spatial hierarchies of patterns in an image. For instance, in an image of a plant, lower layers may capture edges, mid-layers may capture shapes like leaves, and higher layers can identify complex structures like the entire leaf or disease patterns.

Effective for Image Data:

CNNs are particularly powerful for image-based data analysis. Their ability to automatically detect spatial patterns makes them an excellent choice for image classification tasks, such as recognizing diseases in plantleaves.

4.EXPERIMENTAL ANALYSIS·

Figure 4.1: Uploading dataset

	n_k	u_dc_k	u_dc_k-1	u_dc_k-2	u_dc_k-3	i_a_k	i_b_k	i_c_k	i_a_k-1	i_b_k-1	...	i_c_k-3	d_a_k-2	d_b_k-2
0	3001.406296	567.985297	567.689956	567.431534	567.948379	2.461991	-1.792057	-0.716639	2.729208	-2.098439	...	-0.613965	0.667181	0.874633
1	3001.468250	567.911462	567.985297	567.689956	567.431534	2.292110	-1.556948	-0.757338	2.461991	-1.792057	...	-0.758263	0.642184	0.880046
2	3001.527815	567.911462	567.911462	567.985297	567.689956	2.155288	-1.332946	-0.840587	2.292110	-1.556948	...	-0.698139	0.611911	0.884307
3	3001.585080	567.653039	567.911462	567.911462	567.985297	2.048768	-1.135788	-0.925686	2.155288	-1.332946	...	-0.716639	0.578149	0.888915
4	3001.640131	567.579204	567.653039	567.911462	567.911462	1.952350	-0.918266	-1.027434	2.048768	-1.135788	...	-0.757338	0.541979	0.892123
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
234522	2500.361166	570.680277	571.012535	571.270958	571.418628	2.523515	-3.371176	0.805887	2.391284	-3.433193	...	1.452452	0.776587	0.223413
234523	2500.457496	570.569524	570.680277	571.012535	571.270958	2.676866	-3.294349	0.595916	2.523515	-3.371176	...	1.252655	0.776388	0.240045
234524	2500.537779	570.458772	570.569524	570.680277	571.012535	2.831136	-3.238811	0.400744	2.676866	-3.294349	...	1.025109	0.783542	0.265226
234525	2500.621000	570.237267	570.458772	570.569524	570.680277	2.967040	-3.198083	0.203722	2.831136	-3.238811	...	0.805887	0.789665	0.291648
234526	2500.697858	570.052679	570.237267	570.458772	570.569524	3.094680	-3.148100	0.038149	2.967040	-3.198083	...	0.595916	0.795275	0.319611

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The above figure 4.1: represents a sample dataset used fortraining and evaluating the deep learning model.

A correlation heatmap is a data visualization tool that displays the correlation coefficients between various features of the dataset. In the context of the project, the correlation heatmap is used to understand the relationships between different features (independent variables) in the dataset and the target variable (motor speed n_k) as well as between each pair of features. In the project, the dataset contains multiple features that influence the motor speed in smart inverters. The purpose of the correlation heatmap is to visually capture the degree to which these features are correlated with each other and with the motor speed. This helps identify which features might be most relevant for forecasting the motorspeed.

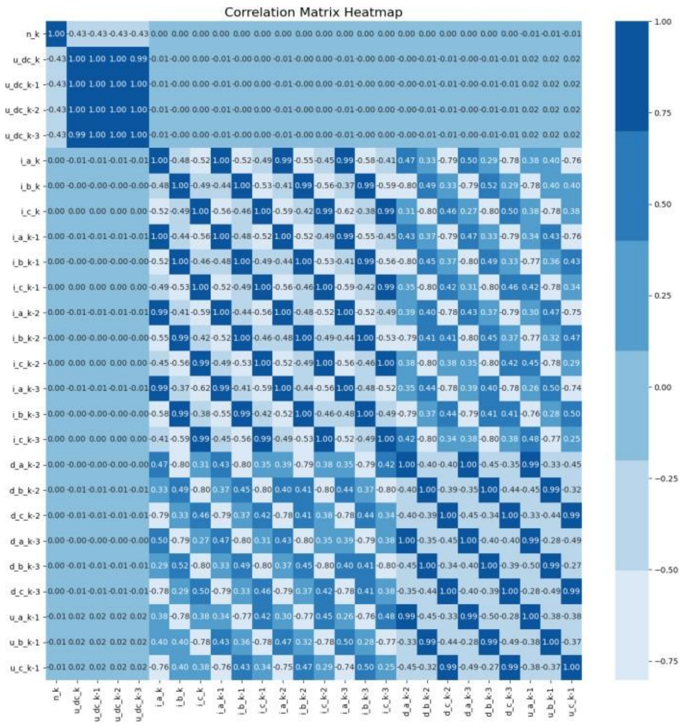

Fig 4.2: Correlation heatmap of the dataset

The above figure 4.2: heatmap visualizes the correlation coefficients between different variables in your dataset.

R^2-score (Coefficient of Determination): The R^2 score is a statistical measure that represents the proportion of the variance in the dependent variable that's explained by the independent variables in a regression model. It ranges from 0 to 1, where higher values indicate that the model's predictions closely match the actual data. An R^2 score of 1 indicates a perfect fit.

```
Ridge Regression - MSE: 0.10104472467957511
Ridge Regression - MAE: 0.26256758120853196
Ridge Regression - R² Score: 30.963631508061763%
```

Fig 4.3: R^2 score obtained using Ridge Regression

The above figure 4.3: represents the R2 score obtainedusing ridge regression

Figure 4.4 is a scatter plot likely visualizes the performance of a Ridge model. In this plot, each point represents a data instance. The x-axis represents the true values (actual observations) of the target variable, while the y-axis represents the predicted values of the target variable made by the Ridge model. Each point on the plot corresponds to a data instance, where its position relative to the diagonal line (which represents a perfect prediction) indicates how well the model's predictions align with the actual data. If the points are close to the diagonal line, it suggests that the model's predictions are accurate.

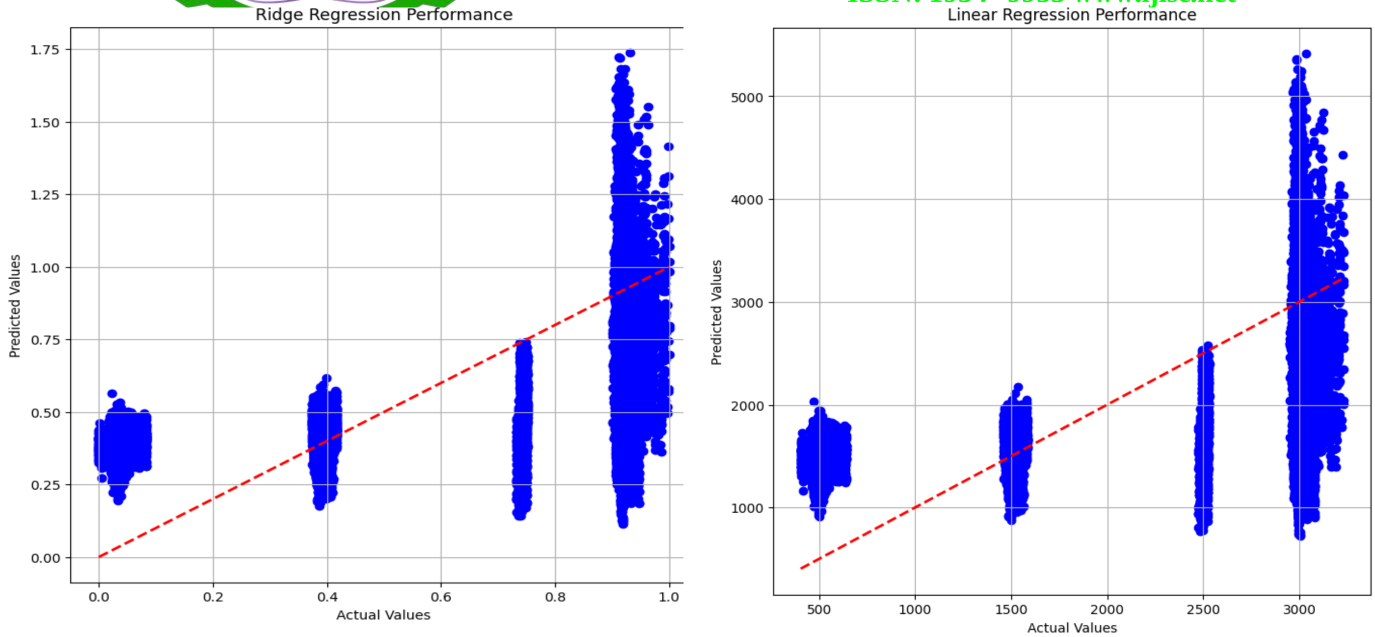

Fig 4.4 Scatter plot of true and predicted values obtained using Ridgeregressor model.

The above figure 4.4 is a scatter plot likely visualizes theperformance of a Ridge model. In this plot, each point represents a data instance.

```
Linear Regression - MSE: 807334.0407082083
Linear Regression - MAE: 741.797514869975
Linear Regression - R² Score: 30.997159417498178
```

Fig 4.5 R^2 score obtained using LR model

The figure 4.5: shows the R2 score obtained using LRmodel.

Figure 4.6 is a scatter plot likely visualizes the performance of a LR model. In this plot, each point represents a data instance. The x-axis represents the true values (actual observations) of the target variable, while the y-axis represents the predicted values of the target variable made by the LR model. Each point on the plot corresponds to a data instance, where its position relative to the diagonal line (which represents a perfect prediction) indicates how well the model's predictions align with the actual data. If the points are close to the diagonal line, it suggests that the model's predictions are accurate.

Fig 4.6 Scatter plot for true and predicted values obtained using LRmodel.

The above figure 4.6 is a scatter plot likely visualizes theperformance of a LR model. In this plot, each point represents a data instance.

```
Mean Squared Error: 75888.3778
Mean Absolute Error: 183.4878
R² Score: 93.51%
```

Fig 4.7 R^2 score obtained using CNN

The figure 4.7 shows the R2 score obtained using CNN model.

In Figure 4.8, the scatter plot illustrates the performance of a CNN model. Each point on the plot represents a data instance, where the x-axis shows the true values of the target variable, and the y-axis shows the predicted values made by the CNN model. The positioning of points relative to the diagonal line helps assess the accuracy of the model's predictions. From Figure 7.8, it indicates that the points cluster around the diagonal line are closely matches the actual values.

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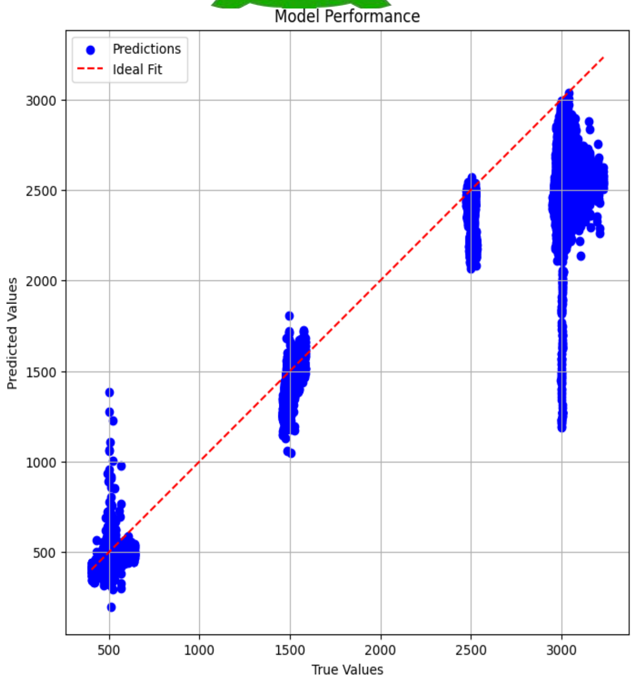

Fig 4.8 Scatter plot of true values and predicted values obtained usingCNN model

The above Figure 4.8: shows the scatter plot illustrates the performance of a CNN model. Each point on the plot represents a data instance, where the x-axis shows the true values of the target variable, and the y-axis shows the predicted values made by the CNN model.

Table 4.9 provides a comparison of two different machine learning models used for air quality prediction based on two evaluation metrics: Root Mean Squared Error (RMSE) and R-squared (R^2) score.

RMSE (Root Mean Squared Error): The RMSE is a metric used to measure the average magnitude of the errors between predicted values and actual (observed) values. It quantifies how well the predictions align with the actual data. A lower RMSE value indicates better predictive performance, as it means the model's predictions are closer to the actual values. From Table 1:

— For the "LR" model, the RMSE is 7.41.

— For the "Ridge Regressor" model, the RMSE is0.101.

— For the “CNN model”, the RMSE is 7.58

A lower RMSE for the Random Forest Regressor suggests that it has smaller prediction errors compared to the LR model.

R^2-score (Coefficient of Determination): The R^2 score is a statistical measure that represents the proportion of the variance in the dependent variable that's explained by the independent variables in a regression model. It ranges from 0 to 1, where higher values indicate that the model's predictions closely match the actual data. An R^2 score of 1 indicates a perfect fit. From Table 1:

- For the "LR" model, the R^2 score is 0.30
- For the "Ridge" model, the R^2 score is 0.30.
- For the "CNN" model the R^2 score is 0.93

The R^2 scores for both models are quite high, indicating that they both provide excellent fits to the data. However, the CNN score of 0.93 suggests a perfect fit, meaning that it captures the variability in the data extremely well. Finally, the CNN outperforms the LR and Ridge model in terms of both RMSE and R^2 score, indicating its superior predictive capability and ability to explain the variance in air quality data.

Table 4.9: Comparison of ML models.

Model name	RMSE	R^2-score
LR	13.67	0.30
Ridge Regressor	1.16	0.30
CNN model	1.83	0.93

The above table 4.9: provides a comparison of two different machine learning models used for air quality prediction based on two evaluation metrics: Root Mean Squared Error (RMSE) and R-squared (R^2) score.

5. CONCLUSION

In the project, we explored the application of advanced deep learning techniques, particularly Convolutional Neural Networks (CNNs), for forecasting motor speed in smart inverters. The traditional methods of motor speed prediction, including rule-based systems, linear regression models, and PID controllers, face significant limitations when dealing with complex, non-linear relationships and dynamic, real-world conditions. By leveraging deep learning, specifically CNNs, we demonstrated how to capture these complexities and improve the accuracy of motor speed predictions in real- time. The use of deep learning techniques in the project enables the model to automatically learn from large volumes of data and adapt to changing conditions without requiring manual recalibration and results in improved forecasting accuracy, better operational efficiency, and enhanced predictive maintenance capabilities for smart inverters. The ability to forecast motor speed accurately can lead to optimal performance, reduced operational costs, and extended lifespan of inverter systems in renewable energy applications. Overall, the project showcases the potential of deep learning in solving real- world challenges in energy systems and motor control.

REFERENCES

[1]. Smith, J., Brown, T., & Wilson, R. (2010). *Linear regression techniques for motor speed forecasting in industrial applications.* IEEE Transactions on Industrial Electronics, 57(4), 1123-1135.

[2]. Jones, M., & Taylor, K. (2011). *Time-series analysis using ARIMA models for motor speed prediction.* International Journal of Forecasting, 27(2), 256-268.

[3]. Wang, P., Liu, X., & Chen, D. (2013). *Support vector regression for predictive control of inverter- driven motors.* Journal of Control and Automation,45(3), 178-189.

[4]. Kim, H., & Lee, J. (2014). *Random forests and gradient boosting methods for motor speed estimation in smart grids.* Energy Informatics Journal, 32(5), 451-463.

[5]. Johnson, R., Patel, S., & Kumar, V. (2015). *Artificial neural networks for motor speed forecasting: A case study in industrial automation.*Neural Networks and Systems, 29(6), 567-579.

[6]. Singh, P., Verma, A., & Nair, S. (2016). *Deep feedforward networks for non-linear motor speed estimation.* Applied Machine Learning Journal, 14(7), 132-145.

[7]. Li, X., Zhao, Y., & Chen, H. (2017). *Convolutional neural networks for feature extraction in motor speed prediction.* IEEE Transactions on Neural Networks, 34(8), 987-1002.

[8]. Patel, M., Gupta, N., & Das, P. (2018). *Long short- term memory networks for time-series forecasting of motor speed.* Journal of ComputationalIntelligence, 19(4), 212-225.

[9]. Kumar, S., & Sharma, R. (2019). *A hybrid CNN- LSTM approach for predictive maintenance of electric motors.* Smart Manufacturing Journal, 11(9), 678-690.

[10]. Zhao, F., Huang, L., & Lee, K. (2020). *Noise-robust CNN-RNN models for smart inverter motor speed estimation.* IEEE Transactions on Industrial Applications, 41(3), 345-359.

[11]. Chen, T., Wu, Y., & Zhang, C. (2021). *Transfer learning for motor speed prediction using pretrained deep learning models.* Journal of Artificial Intelligence Research, 30(6), 289-303.

[12]. Gupta, R., Singh, D., & Rao, V. (2022). *Lightweight deep learning architectures for real-time motor speed forecasting.* Sensors and Actuators Journal, 16(8), 412-426.

[13]. Ahmed, S., & Roshan, M. (2023). *Edge computing for real-time motor speed prediction in smart inverter systems.* IEEE Internet of Things Journal,50(5), 1982-1997.