WIND ENERGY POTENTIAL MAPPING IN INDIA

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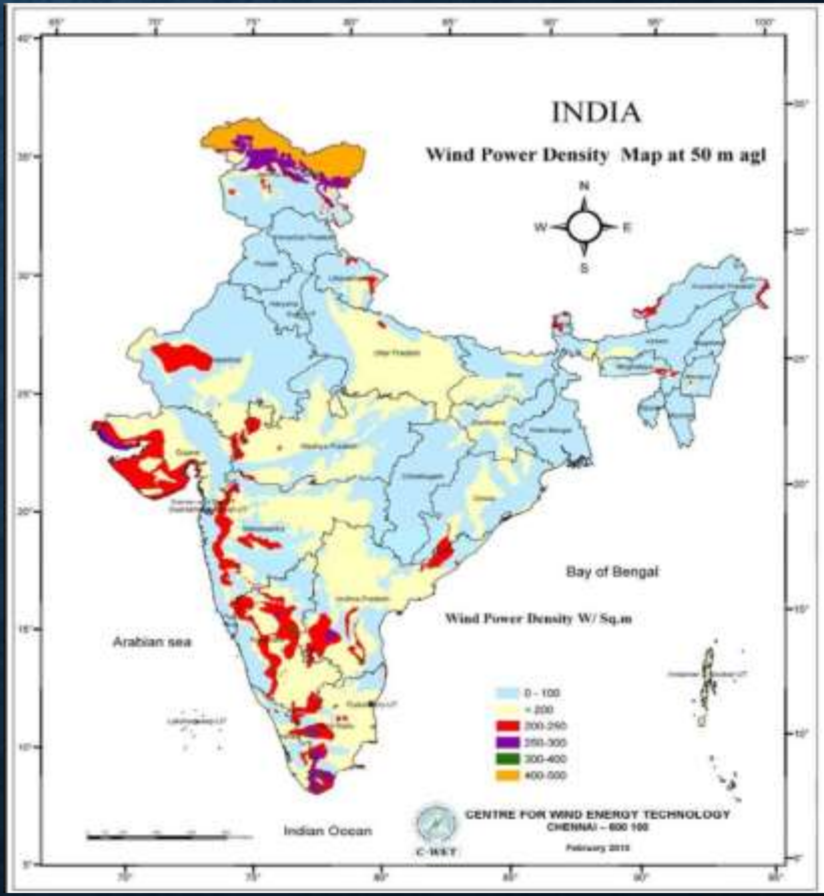


WHY ARE WE WORKING WITH WIND ENERGY?

- Non-renewable energy sources like coal and oil are depleting, increasing the demand for renewable energy.
- India is the fourth-largest wind energy producer, with over 44 GW installed capacity.
- Global wind power generation grew by 10% in 2017.
- Government initiatives like the Wind-Solar Hybrid Policy and financial incentives support India's wind energy sector.
- Accurate wind power forecasting is essential for affordable and reliable energy supply.

OBJECTIVE OF THE PROJECT

- **Dataset for Wind Farm Site Selection:** Create a dataset with random geographic points and key environmental variables (wind speed, elevation, distance to coastlines) to optimize wind farm site selection.

- **Assessment of Wind Energy Potential:** Analyze wind speed, elevation, and proximity to coastlines across Indian states using geospatial data to identify high-potential regions for wind energy development.

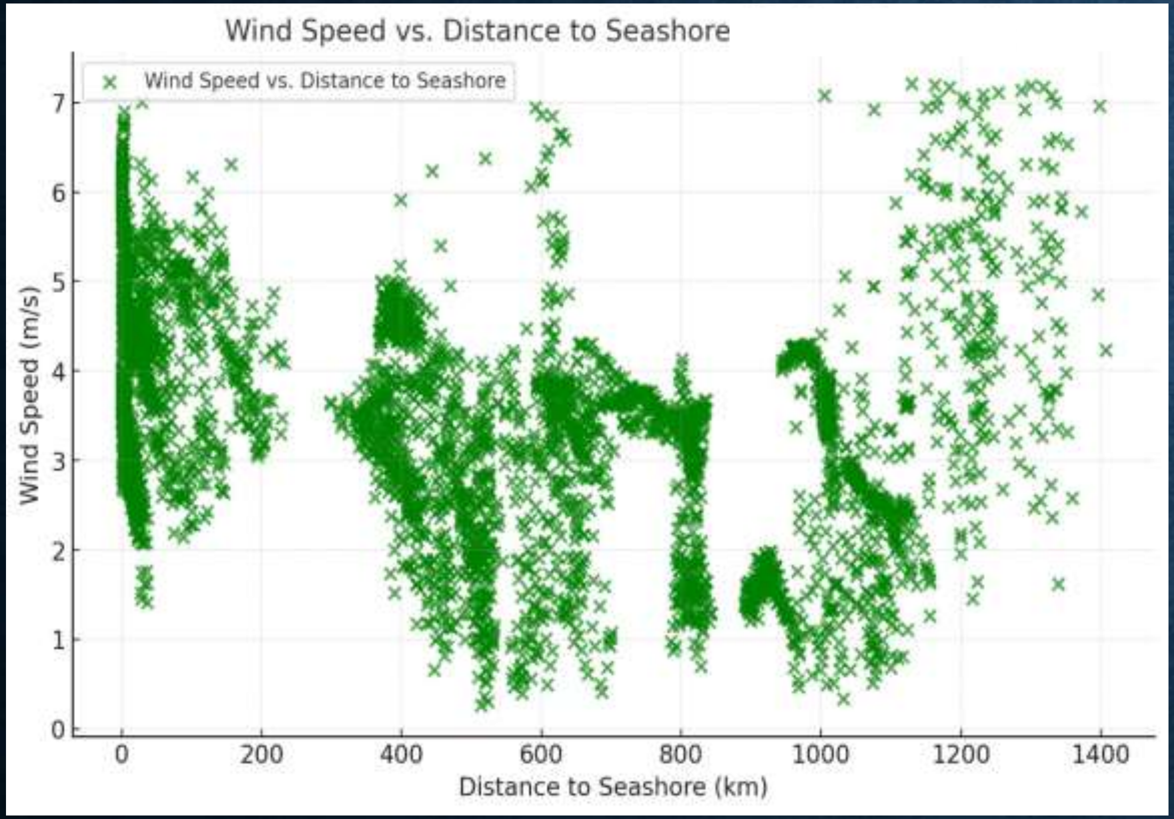
DATASET CREATION AND EXTRACTION

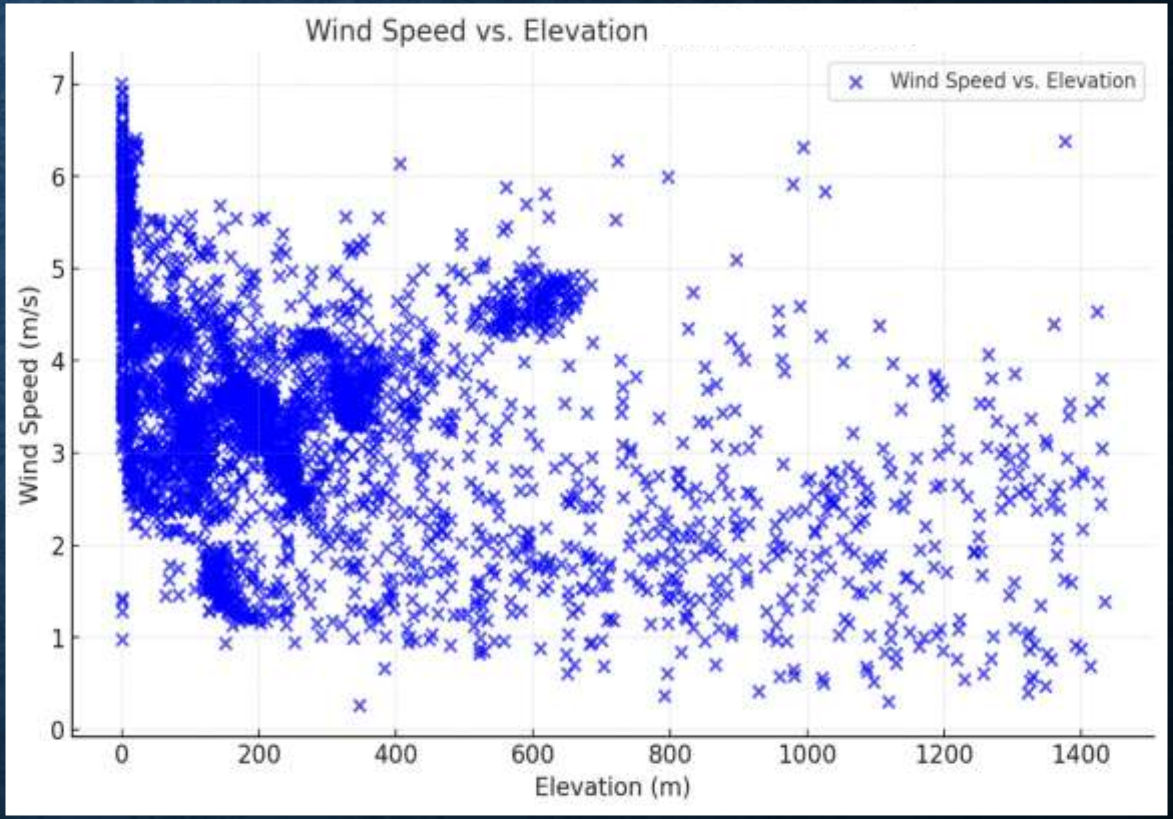
- **Data Development in Python:** Geographic and meteorological data specific to India were processed using Python.
- **Shapefile Integration:** A shapefile (.shp) outlined India's geography, storing attributes like elevation, wind speed, and weather characteristics.
- **TIFF Data Extraction:** Raster files (TIFF) were used to extract environmental data, such as surface temperatures and elevation, using Python's Raster library.
- **Coastal Proximity Analysis:** Another shapefile was used to calculate the distance of data points from India's coastline.
- **Sampling and Storage:** 100 random data points were generated for each state/UT, with all data stored systematically in a CSV file for analysis.

THE DATASET

STATE	longitude	latitude	wind_speed (m/s)	distance_to_seashore (km)	elevation (m)	temperature (C)	humidity (%)	air_density (kg/m^3)
JAMMU AN	75.81578	34.456748	5.4057374	1339.35001	3798	21	65	1.12
JAMMU AN	76.795108	33.479497	4.9437666	1293.852416	4303	21	65	1.12
JAMMU AN	75.439667	34.391441	3.78182	1319.563054	4338	21	65	1.12
JAMMU AN	75.793579	34.12264	8.870201	1304.484655	5037	21	65	1.12
JAMMU AN	77.46023	32.819307	3.263829	1246.270083	4624	21	65	1.12
JAMMU AN	76.593671	33.585248	8.518707	1299.334511	5581	21	65	1.12
JAMMU AN	76.684974	33.485512	6.921151	1291.372698	5199	21	65	1.12
JAMMU AN	75.458691	34.517125	3.7869701	1333.179858	4081	21	65	1.12
JAMMU AN	75.807141	34.425869	4.528658	1335.886372	3069	21	65	1.12
JAMMU AN	77.189485	32.919688	7.318989	1247.428044	5317	21	65	1.12
JAMMU AN	76.407198	34.121138	5.5047393	1328.050978	5161	21	65	1.12

MAJOR FEATURES IN THE DATASET





PROPOSED SOLUTION

- The wind speed, topographical, and environmental data is split into 80% training and 20% testing datasets for model validation.

- A feedforward neural network is used to predict high wind-speed areas using features like elevation, latitude, and other features available.

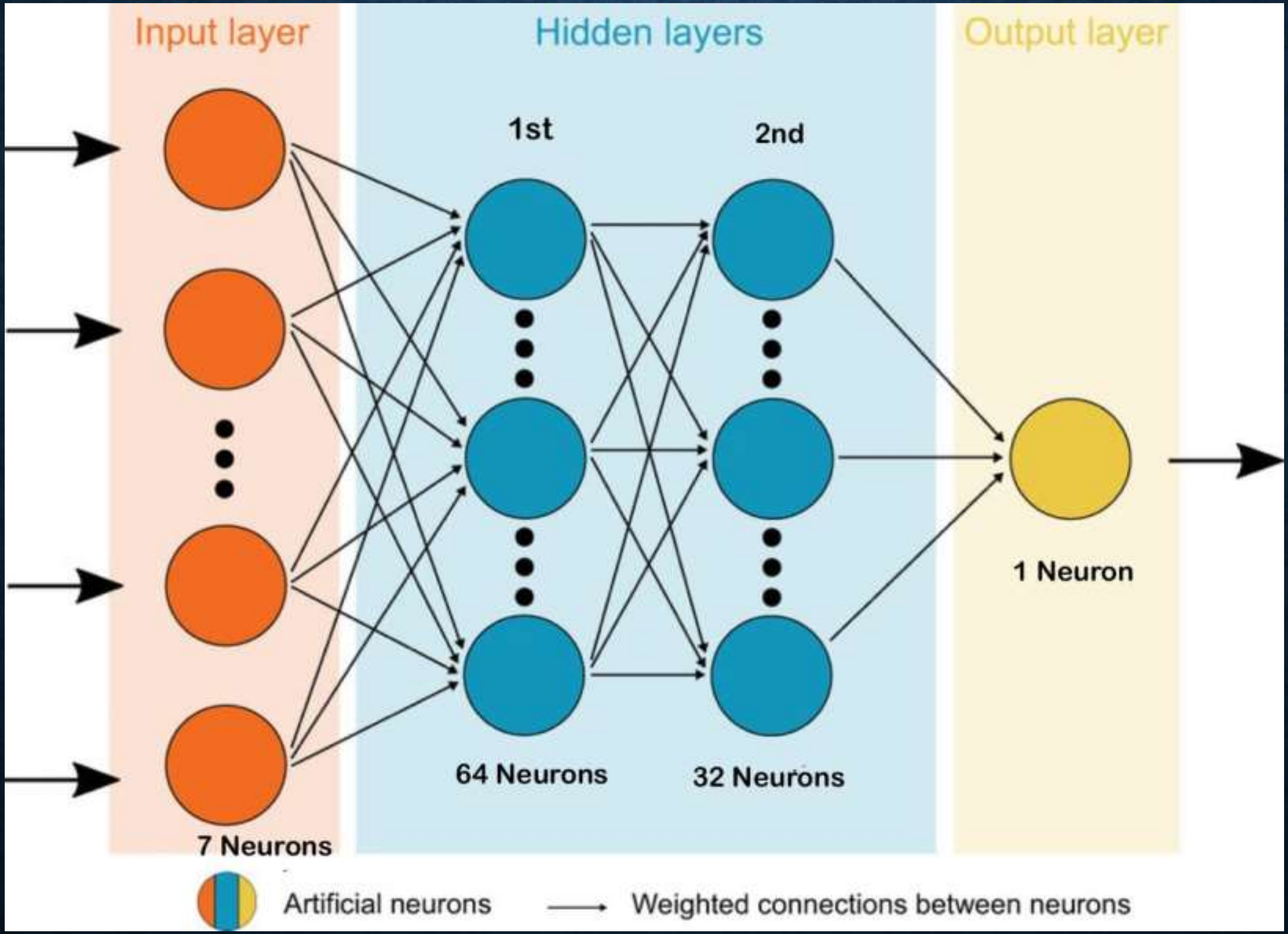
- Identify regions meeting wind speed thresholds.

- Validate predictions against historical data, to verify results.

EXPERIMENTAL PROCEDURE

- **Input Features:** The model takes features like longitude, latitude, distance to seashore, elevation, temperature, humidity, and air density as input.
- **Feature Processing:** These inputs are processed through hidden layers to learn patterns and relationships using non-linear transformations.
- **Output Prediction:** The final layer outputs the predicted wind speed in meters per second.
- **Learning and Optimization:** The model minimizes prediction errors during training using the Adam optimizer and Mean Squared Error loss.

MODEL ARCHITECTURE DIAGRAM



MODEL ARCHITECTURE

- A feedforward neural network with three layers: an input layer matching dataset features, two hidden layers (64 and 32 neurons, ReLU activations), and an output layer producing a single continuous value for regression tasks.

- Uses the Adam optimizer for dynamic learning rate adjustment, Mean Squared Error (MSE) as the loss function, and Mean Absolute Error (MAE) as the evaluation metric.

- Trained for 80 epochs with a batch size of 16 using 20% of training data for validation to monitor performance and mitigate overfitting.

- Assessed on a test set with MSE and MAE, providing measures of model accuracy and interpretability in regression.

- Non-linear ReLU activations for learning complex patterns, compact two-layer design for computational efficiency, and robust optimization for stable learning.

EXPERIMENTAL RESULTS

Accuracy	**85%**
Mean Absolute Error (MAE)	**0.45**
Mean Squared Error (MSE)	**0.49**
Root Mean Squared Error(RMSE)	**0.70**
R^2	**0.78**
Mean of target variable	**3**

CONCLUSION

Here in this work, we present an ML-based model that will predict the wind speed of a certain location based on the aforementioned features.

Experimental results are promising with **85% accuracy**.

We like to extend our work by gathering more data and would like to consider Solar exposure.

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THANK YOU!