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AI-Driven Spatiotemporal Mapping and Grid Optimization for Solar and Wind Energy

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INTRODUCTION & AIM

Reduction in carbon emissions and combating climate change depend on renewable energy—especially solar and wind energy. Driven by location, seasons, weather, and cli- mate, these fluctuations provide difficulties for consistent generation. Whereas wind energy depends on speed, direction, and turbulence, solar power depends on radiance, cloud cover, and sunshine angle etc. Predicting energy output, improvement in grid stability, and optimizing the storage, artificial intelligence (AI) and machine learning (ML) offer innovative results. For accurate prediction solar and wind potential, artificial intelligence models examine topo- graphical factors, meteorological data, satellite images, GIS- based spatial data required. ML picks intricate patterns, un- like deterministic models, therefore enhancing the accuracy of resource mapping. When artificial intelligence (AI) is added to geographic information systems (GIS), accurate mapping is possible, which helps to find the best places for green energy installations hence minimizing environmental conflicts. By use of energy supply and demand analysis, GIS helps dynamic grid management. AI-powered smart grids and storage systems keep supply and demand in balance, and predictive analytics make them more efficient. Deterministic models are generally used in traditional resource mapping, Due to this maps are less accurate. AI-driven methods combine several information to provide accurate evaluations, thereby optimizing grid operations and infrastructure placement for sustainability. Mapping Solar and Wind Energy: Potential Current methods use physical models and weather data, like the Solar and Wind Energy Resource Atlas, but struggle with complex datasets. Machine Learning to assess India's solar potential using land-use and irradiance data. Over 20% of U.S. power comes from renewables, as shown in Fig. 1.

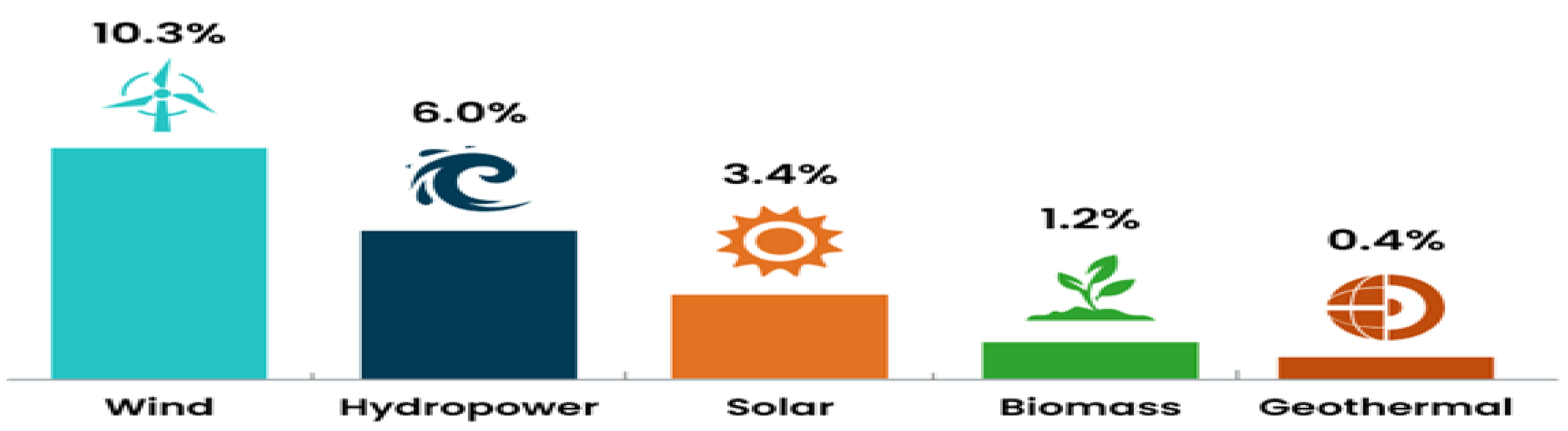

Fig. 1. Renewable Energy in the United States [16]

GIS aids resource mapping and infrastructure planning by evaluating land characteristics. Combining ML with GIS for predicting microgrid energy supply patterns.

METHOD

Renewable energy sources are essential for energy production and energy transfer systems. In this paper, we explore a novel approach that combines natural and social sciences through a machine learning (ML) technique, which integrates environmental and geographical information systems (GISs) and aligns with the United Nations' 17 Sustainable Development Goals (SDGs). With the help of a dataset, we derived one hundred regional observations that covered solar irradiation, wind energy, temperature, relative humidity, and altitude. Then, we enhanced this dataset using GIS information (latitude and longitude) and available energy production information at historical timestamps. This dataset was used for training the neural network. With the help of TensorFlow's Sequential Application Programming Interface (API), we used dropout regularisation

A. **Data Collection & Pre-processing:** Collect and clean meteorological data (irradiance, wind, temperature, cloud cover) from NASA/NOAA or local stations, fixing missing values and normalizing features.
B. **Feature Engineering:** Extract features across solar (GHI, DNI, cloud cover), wind (multi-level wind speed, air density, turbulence), and geo-spatial factors (latitude, longitude, elevation, land type).
C. **Machine Learning Model Development:** We use a deep neural network to predict renewable energy potential because it captures complex nonlinear patterns and automatically learns rich feature representations better than traditional ML methods.
D. **GIS Integration for Spatial Mapping:** Use Geo-Pandas and Folium for spatial visualization. Overlay predictions on GIS maps, generating heatmaps of energy potential. Generate heatmaps indicating high-potential solar and wind energy zones
E. **Grid Optimization Decision Support:** Simulate energy demand vs. supply using optimization models. Suggest optimal locations for new renewable energy plants based on model predictions. Evaluate potential grid integration strategies to reduce energy loss.
F. **Model Validation & Deployment:** Use cross-validation for accuracy and deploy via APIs for real-time predictions.

RESULTS & DISCUSSION

To evaluate neural network approach for renewable energy potential prediction, conducted a comprehensive experiment using a controlled dataset that simulates realistic environmental and geographical conditions. A synthetic dataset of 100 geographic regions was created, featuring uniformly distributed latitudes (25°–45°N) and longitudes (70°–95°E). Each region includes environmental factors such as solar irradiance (5.2 kWh/m²/day), wind speed (7.4 m/s), temperature (23.5°C), and humidity (62%), along with a topographical attribute of altitude (avg. 450 m). The target variable was generated using a non-linear function of these parameters with added noise, expressed in MWh. The model was trained using standardized features, an 80/20 train-test split, and Adam (LR=0.001) with MSE loss for 50 epochs. Training loss dropped from 98,273 to 16,651, while validation loss declined from 75,192 to 22,756, where it stabilized.

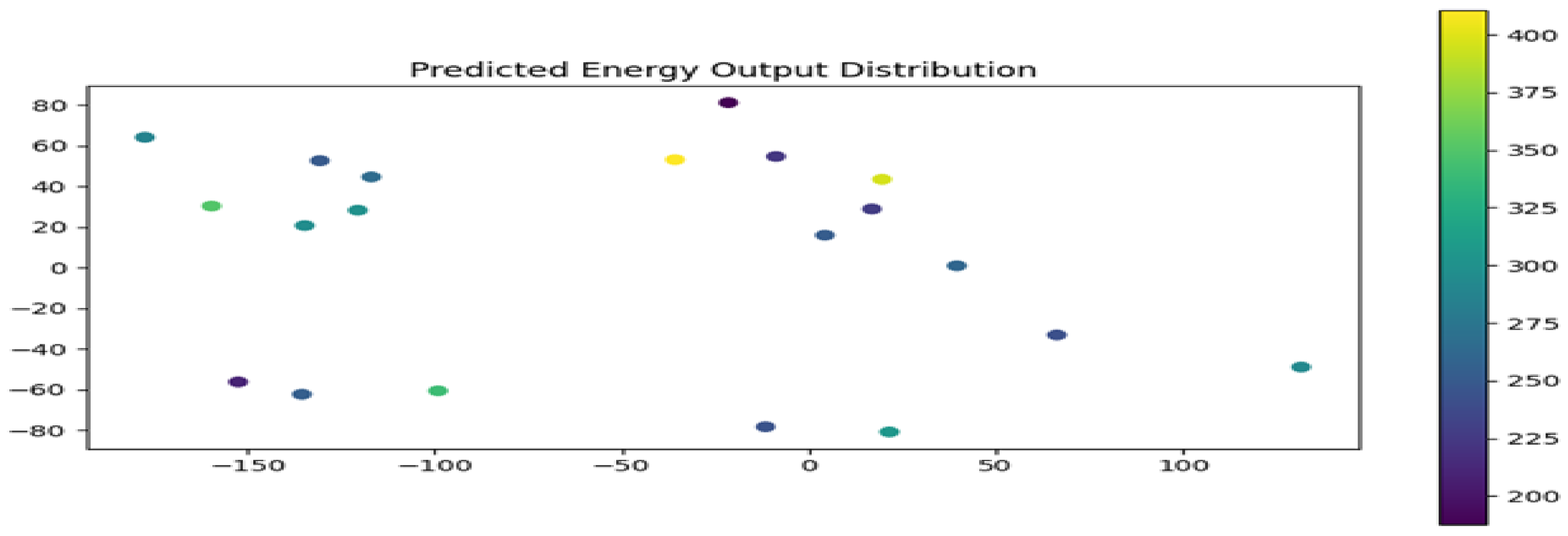

Fig. 2. Predicted Energy Output Distribution

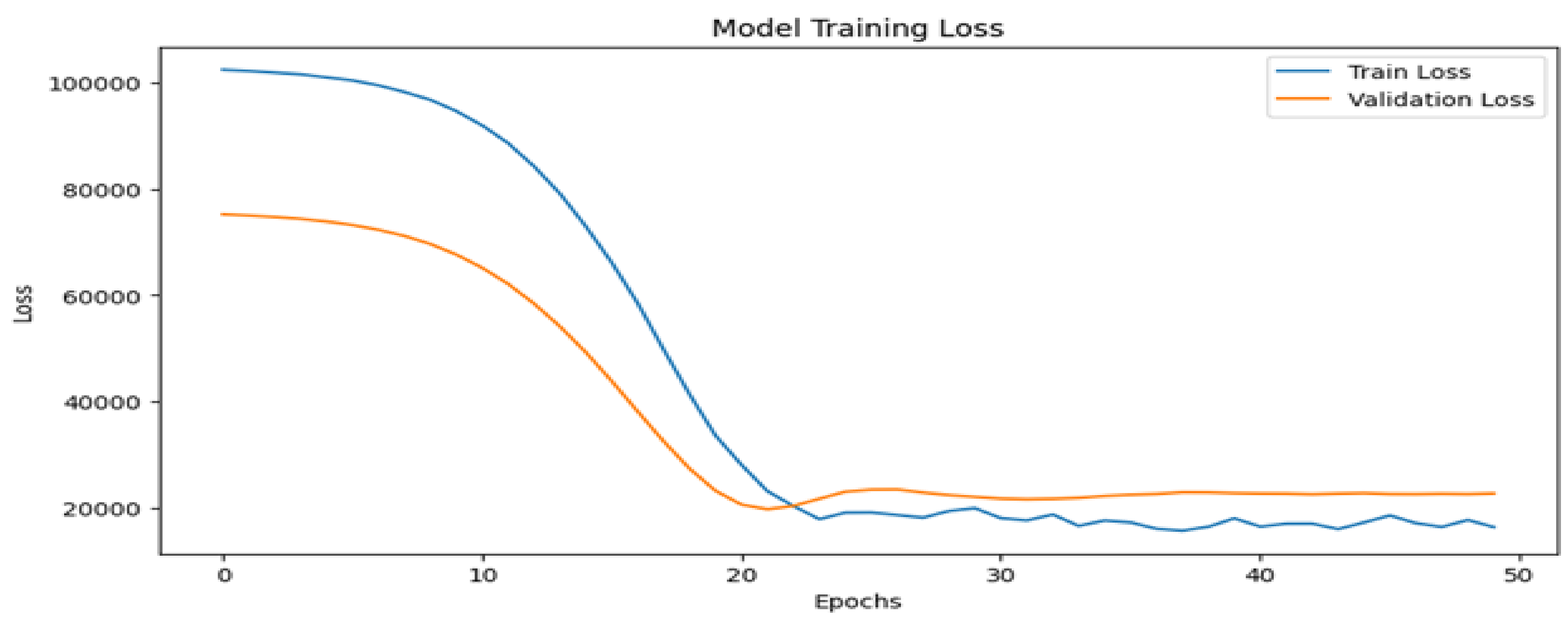

Fig. 3. Epochs vs. Loss

Test MSE was 22,756. Spatial analysis using GeoPandas mapped predicted energy outputs, revealing clear regional clusters and latitude-based patterns, with higher potential in lower latitudes and noticeable effects of altitude and local conditions. Feature importance showed solar irradiance as the dominant factor, followed by wind speed and coordinates, and loss curves confirmed convergence after around 25 epochs.

CONCLUSION/ FUTURE WORK

Our research integrates GIS with machine learning to accurately map and forecast renewable energy potential. The proposed neural model analyzes environmental and terrain factors to predict energy output and presents the results through clear, interpretable spatial visualizations. With standardization and dropout ensuring robust, non-overfitted performance, the framework is well-suited for real-world applications. It offers practical value for grid operators, policymakers, and energy planners by improving resource assessment, optimizing allocation, and enhancing grid stability. By combining GIS and deep learning, the work supports smarter and more efficient renewable energy systems, demonstrating how AI can address complex forecasting challenges and guide future sustainable energy planning.

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