Project Midway Report

Predicting Hurricane Categories Using Machine Learning

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1. Introduction

Predicting hurricane categories accurately is crucial for preparing and responding to natural disasters. This allows emergency management to allocate resources and issue timely warnings to affected areas. Recent extreme weather events, such as Hurricane Helene's impact on the southeastern United States, have underscored the necessity for improved hurricane forecasting models. Traditional meteorological models can be limited in their ability to account for complex, non-linear relationships between climate factors. Machine learning (ML) models offer a data-driven approach to capture these intricate patterns, potentially enhancing predictive capabilities.

The goal of this project is to classify hurricanes by category using NOAA's Atlantic Hurricane Database (HURDAT2), supplemented with recent data sources that capture environmental factors such as rising sea surface temperatures and atmospheric pressure variations. These additional factors are anticipated to improve model accuracy, particularly for high-intensity hurricanes, whose characteristics may be increasingly influenced by warming ocean waters. The primary objectives are to develop a machine learning model that accurately categorizes hurricanes, explore the impact of including environmental data in these predictions, and analyze the performance of different machine learning techniques. This project will ultimately provide valuable insights for meteorological research and disaster preparedness strategies.

2. Related Work

Hurricane forecasting traditionally relies on physics-based models that simulate storm behavior based on physical principles, such as the conservation of energy and momentum. These models are adept at capturing storm dynamics but are limited by computational requirements and often struggle with the variability introduced by climate change. In recent years, data-driven methods have gained traction for their ability to identify complex, non-linear relationships in large datasets. These methods include statistical models and, more recently, machine learning techniques.

Several machine learning approaches have been explored for hurricane prediction. Random Forests and Gradient Boosting models are among the most commonly used ensemble methods in meteorological data analysis, as they handle non-linear relationships well and can effectively capture interactions between features. However, these models may not fully capture the temporal evolution of storms. Artificial Neural Networks (ANNs), particularly when configured with deep architectures, can manage complex datasets with high dimensionality and varying feature interactions, making them suitable for applications in meteorology.

Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), have proven valuable for sequential data, as they can model temporal dependencies in storm progression, capturing dynamic changes in intensity as a storm moves. Studies have demonstrated the utility of LSTMs in predicting hurricane intensity by retaining the sequential nature of data points, such as six-hourly measurements of wind speed and pressure. By retaining this temporal structure, LSTMs can capture complex, time-dependent patterns that are often indicative of storm category.

Beyond supervised learning, unsupervised techniques have been applied to analyze patterns within storm data, providing an exploratory means to understand underlying structures and similarities among storms of varying intensity. This project integrates insights from these methodologies, combining both supervised and unsupervised learning approaches to analyze hurricane data and derive meaningful patterns.

3. Methods

Data Collection and Preprocessing

Our primary data source, NOAA's HURDAT2, provides six-hourly storm measurements across several meteorological attributes, including wind speed, pressure, and geographical coordinates. To account for recent changes in climate that may influence storm intensity, we supplement this dataset with two years of data on sea surface temperatures and atmospheric pressure variations, two factors closely linked to storm development and severity.

The data preprocessing pipeline includes several critical steps. First, we handle missing values, particularly in earlier data, using imputation methods such as forward-filling for time-sequenced data and mean imputation for isolated missing values. We then scale the data using standardization to ensure consistency across features, particularly those with different measurement scales, like temperature (in °C) and wind speed (in knots). Feature selection and engineering are performed to extract the most relevant variables, including derived features like storm speed and change rates in wind speed and pressure over time.

Model Architecture

The primary model used in this project is an Artificial Neural Network (ANN) with three hidden layers (64, 32, and 16 nodes), chosen for its capacity to handle complex interactions in the dataset. The model uses ReLU activation functions in the hidden layers to introduce non-linearity, which is essential for capturing complex relationships among meteorological and environmental features. A softmax output layer is used for multi-class classification, enabling the model to predict across the various hurricane categories. Input features include atmospheric pressure, sea surface temperature, wind speed, and derived temporal features. Each input is standardized to facilitate training convergence.

Training was conducted over 50 epochs with a batch size of 16. The model was optimized using the Adam optimizer and categorical cross-entropy loss function, given the multi-class nature of the task. Early stopping was implemented to prevent overfitting, and validation performance was monitored across epochs. Hyperparameter tuning, including adjustments to layer sizes and learning rate, was performed iteratively to improve model performance on both training and validation data.

In addition to the supervised ANN model, we apply unsupervised learning to identify potential clusters in the storm data that might reveal patterns correlated with storm intensity and progression. By employing k-means clustering, we aim to explore latent features that could provide additional insights into how environmental factors, such as rising water temperatures, might affect storm categorization.

Evaluation Metrics

Model performance is evaluated using accuracy, precision, recall, and the ROC-AUC score, providing a well-rounded view of classification effectiveness across hurricane categories. Given the imbalance in hurricane categories, particularly the relative rarity of higher categories, these metrics ensure that model accuracy is not skewed by over-representation of lower-intensity storms. In the unsupervised approach, we evaluate clustering effectiveness using silhouette scores, providing insight into the distinctiveness of clusters based on storm intensity.

4. Preliminary Results

Initial results from the two-year dataset indicate that the ANN model achieves a test accuracy of approximately 69.39%, with training and validation accuracies stabilizing around 68% and 67.5%, respectively. This accuracy level suggests that while the model is effective for lower-category hurricanes, challenges remain in classifying higher categories, likely due to their underrepresentation in the dataset. Analysis of feature importance reveals that sea surface temperature significantly contributes to the model's accuracy, particularly in distinguishing between high and low-intensity storms. Temporal patterns captured through pressure changes over time also play a critical role in classification.

Early results indicate that storms with higher sea surface temperatures tend to cluster in higher categories, suggesting a potential link between climate factors and storm intensity. This finding aligns with recent research on climate change's influence on hurricanes and highlights the value of including environmental data in predictive modeling. These unsupervised insights will be further validated with a larger dataset and additional clustering metrics.

5. Future Plans

The next stage of this project includes further hyperparameter tuning and experimentation with additional architectures, such as LSTMs, to evaluate temporal dependencies. Expanding the dataset with additional years and incorporating more environmental variables will help address the challenge of category imbalance. Furthermore, incorporating seasonal variables, such as month and oceanic region, is anticipated to improve model sensitivity to regional and seasonal hurricane characteristics.

The project timeline for the next phase is as follows: model refinement and additional feature engineering in the next week, extensive testing and validation will begin the following week. The final week will be finalizing the findings and report writing. The final report will present a comparative analysis of supervised and unsupervised approaches, discussing the implications of environmental factors on hurricane intensity and offering insights into the efficacy of machine learning techniques for this application.

By integrating insights from supervised classification and unsupervised clustering, this project aims to provide a comprehensive model for hurricane categorization. These findings will contribute to ongoing research on climate impact on hurricanes and offer a valuable resource for meteorological research and emergency management.

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