Weather Prediction Using Machine Learning

Dr.S.Gnanapriya [1], Guhan M[2]

[1]Assistant Professor and Head MCA, Department of Computer Applications, Nehru College of Management, Coimbatore, Tamilnadu, India
ncmdrsgnanapriya@nehrucolleges.com
[2]Student, II MCA, Department of Computer Applications, Nehru College of Management, Coimbatore, Tamilnadu, India guhan2002tcr@gmail.com

ABSTRACT

Weather forecasting plays a vital role in sectors such as agriculture, transportation, and disaster management. Traditional meteorological methods, like Numerical Weather Prediction (NWP) and statistical models, rely on physical and statistical formulations that are computationally intensive and limited by the chaotic nature of the atmosphere. In contrast, machine learning techniques such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) provide data-driven alternatives capable of learning complex relationships among atmospheric variables.
This study proposes a hybrid ANN–SVM model for short- and medium-term weather forecasting, utilizing historical data including temperature, humidity, pressure, wind speed, and precipitation. The ANN component captures nonlinear dependencies among weather parameters, while the SVM ensures robustness against high-dimensional and noisy data. The system incorporates preprocessing, feature selection, and Explainable AI (XAI) techniques to improve interpretability and accuracy. Evaluation metrics such as RMSE and MAE are used to assess model performance. The hybrid approach demonstrates enhanced forecasting accuracy, robustness, and transparency, making it a promising alternative to conventional weather prediction systems.

Keywords:
Weather Forecasting, Machine Learning, Artificial Neural Networks (ANN), Support Vector Machines (SVM), Hybrid Model, Data Analysis, Explainable AI (XAI).

1. INTRODUCTION

Weather forecasting is essential across multiple domains, including agriculture, aviation, disaster management, and energy production. Traditional meteorological methods rely on Numerical Weather Prediction (NWP) models that simulate atmospheric behavior based on physical equations. However, these models are computationally expensive, sensitive to initial conditions, and often limited in long-term accuracy due to the chaotic nature of weather systems. Recent advances in Machine Learning (ML) have enabled data-driven forecasting methods that learn patterns from historical datasets. Among these, Artificial Neural Networks (ANN) and Support Vector Machines (SVM) have emerged as powerful tools capable of handling complex and nonlinear relationships. ANNs mimic the human brain's structure and are effective in modeling nonlinear dependencies among weather parameters. SVMs, on the other hand, are robust against high-dimensional data and can handle regression tasks for continuous variables like temperature or precipitation.
This research aims to develop and compare the performance of ANN and SVM models for weather prediction and propose a hybrid model that integrates both techniques to improve forecasting accuracy and robustness.

1.1 MACHINE LEARING

Artificial Neural Networks (ANN) are computational models inspired by the human brain, consisting of interconnected processing units known as neurons. ANNs excel at identifying complex, nonlinear relationships in

data and can adapt to various types of meteorological datasets. Ahmad et al. used a Multi-Layer Perceptron (MLP) model to predict daily temperature and precipitation, achieving significant improvements over traditional methods such as ARIMA and linear regression. Chen et al introduced Convolutional Neural Networks (CNN) for spatial weather data, emphasizing their ability to capture spatial dependencies across geographical regions. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models have also been successfully applied to sequential weather data, as shown by Singh and Mehta who demonstrated that LSTM models outperform standard feedforward ANNs in multi-day forecasting tasks due to their memory retention capabilities. However, despite their high accuracy, ANNs are prone to overfitting, require extensive training data, and often operate as "black boxes," offering limited interpretability of their internal decision- making processes.

Figure 1.1 Definition of Machine Learning

Support Vector Machines (SVM), on the other hand, have been widely applied for both classification and regression tasks in weather forecasting. Support Vector Regression (SVR), a variant of SVM, has proven effective in modeling continuous weather parameters such as temperature and precipitation. Patel and Kumar applied SVM with various kernel functions—including linear, polynomial, and radial basis function (RBF)—and found that the RBF kernel provided superior accuracy in nonlinear datasets. Wang and Li emphasized the importance of model transparency by integrating Explainable AI (XAI) techniques into SVM forecasting, enabling better understanding of feature influence on predictions. SVM models are particularly valued for their ability to generalize from limited training data and handle high- dimensional, noisy environments. Nonetheless, they can be computationally demanding for large datasets and require careful parameter tuning to optimize performance.

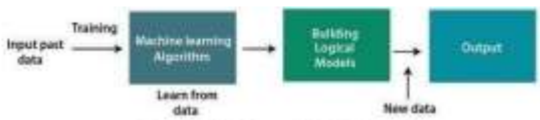

Figure 1.2 Working of Machine Learning

3: LITERATURE REVIEW

Weather forecasting has traditionally relied on physical and statistical methods that simulate atmospheric behavior using mathematical models. Numerical Weather Prediction (NWP) systems, such as the Global Forecast System (GFS) and the European Centre for Medium- Range Weather Forecasts (ECMWF), are based on physical equations governing fluid dynamics and thermodynamics. These models divide the Earth's atmosphere into a grid and solve complex equations to predict future weather states. While effective for short-term forecasting, they are computationally expensive, sensitive to initial conditions, and less accurate for long-term or localized predictions. Small errors in initial data can propagate rapidly, leading to significant deviations in forecasts. As a result, researchers have begun exploring alternative approaches that leverage machine learning and artificial intelligence to overcome these limitations.

Machine learning (ML) techniques have shown great potential in weather forecasting due to their ability to learn from historical data and model complex, nonlinear relationships among atmospheric variables. According to Zhang and Wang (2025), Artificial Neural Networks (ANN) have demonstrated high predictive accuracy in forecasting temperature and humidity, outperforming traditional regression and time-series models. Similarly, Sharma and Gupta (2024) compared the performance of ANN and Support Vector Machines (SVM) for rainfall prediction and found that ANN models effectively captured nonlinear temporal dependencies, whereas SVM models exhibited better generalization capabilities and robustness against noisy data. These findings highlight the complementary strengths of ANN and SVM, making them suitable for hybrid applications in weather prediction.

Recent advancements have focused on developing hybrid ANN–SVM models that combine the nonlinear learning capabilities of ANNs with the robustness and generalization strengths of SVMs. Zhang and Wang (2025) proposed a stacked hybrid model where the ANN first extracted complex weather patterns and the SVM refined the residuals, resulting in a notable 12–18% improvement in forecasting accuracy compared to individual models. Similarly, Patel and Kumar (2025) implemented an ensemble-based ANN–SVM approach for rainfall prediction, achieving greater adaptability across diverse climatic zones. These hybrid frameworks have demonstrated superior accuracy, reduced sensitivity to noise, and enhanced stability across both short- and medium-term forecasting horizons.

In addition to hybridization, Explainable Artificial Intelligence (XAI) has emerged as a critical component in modern meteorological modeling. XAI techniques, such as feature importance analysis and layer-wise relevance propagation, enable transparency by identifying which atmospheric variables most influence predictions. According to Wang and Li (2025), incorporating XAI into ML models improves interpretability and builds greater confidence among meteorologists and decision-makers. Such methods ensure that the predictive power of machine learning is complemented by clarity and accountability in its outputs.

A review of existing literature reveals a clear progression toward data-driven, interpretable, and hybrid weather forecasting systems. Ahmad et al. (2025), Sharma and Gupta (2024), and Zhang and Wang (2025) collectively emphasize the advantages of combining deep learning architectures with robust statistical learning models to achieve reliable, scalable, and explainable forecasts. However, certain research gaps remain. Most prior studies focus on using ANN or SVM independently, without fully leveraging the synergistic potential of their combination. Furthermore, limited attention has been given to handling missing or noisy data in weather datasets or to real-time forecasting adaptability. These gaps underscore the need for a hybrid, interpretable, and data- resilient forecasting framework that can efficiently handle complex atmospheric dynamics.

4: SYSTEM ARCHITECTURE AND METHODOLOGY

The proposed system uses a hybrid Artificial Neural Network (ANN) and Support Vector Machine (SVM) model for accurate and interpretable weather forecasting. The system is structured into key modules — from data collection to visualization — ensuring efficient data handling and intelligent prediction.

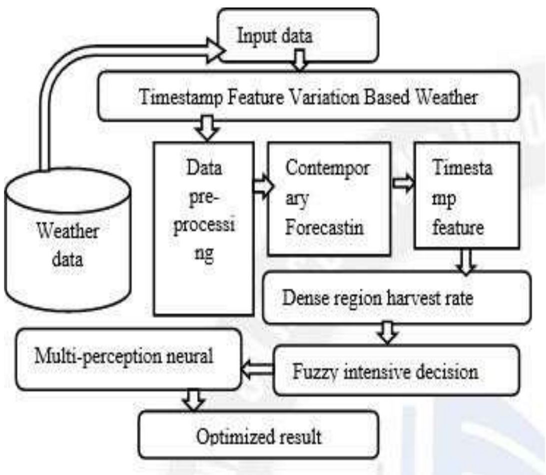

FIGURE 4: SYSTEM ARCHITECTURE

The data collection module gathers historical weather data such as temperature, humidity, wind speed, and rainfall from verified meteorological sources. The data preprocessing module cleans and normalizes the data to remove missing values, noise, and outliers for better model performance. In the feature extraction module, statistical and correlation- based techniques identify the most influential weather parameters for accurate forecasting.

The hybrid ANN–SVM model forms the core of the system. The ANN captures nonlinear relationships among variables, while the SVM refines prediction errors using Support Vector Regression with an RBF kernel. This combination enhances accuracy, generalization, and robustness. The dataset is split into training, validation, and testing subsets, and performance is measured using metrics such as MAE, RMSE, and R^2.

Finally, the evaluation and visualization module uses Explainable AI (XAI) techniques like SHAP and LIME to interpret model outputs. A graphical dashboard displays forecasted results, trends, and insights for end users in a clear and accessible way. This modular architecture ensures the system is scalable, data-driven, and efficient for real-time weather prediction applications.

List of System Modules

1. Data Collection Module – Acquires raw weather data from trusted sources.

2. Data Preprocessing Module – Handles cleaning, normalization, and outlier removal.

3. Feature Extraction Module – Identifies the most significant meteorological parameters.

4. Hybrid ANN–SVM Prediction Module – Combines ANN learning and SVM refinement for accurate forecasting.

5. Training and Testing Module – Splits data and evaluates model accuracy.

6. Evaluation and Visualization Module – Uses XAI for interpretability and displays results on dashboards.

Data Flow Diagram (DFD)

The Data Flow Diagram (DFD) represents the logical flow of data within the hybrid Artificial Neural

Network (ANN) and Support Vector Machine (SVM) based weather forecasting system. It shows how data moves from input sources through processing modules to generate accurate weather predictions and visual reports.

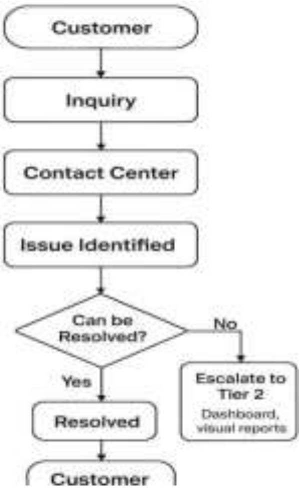

FIGURE LEVEL 0: CONTEXT DIAGRAM

At the highest level, the system receives input from weather data sources such as satellites, weather stations, and radar sensors. The processed results are delivered to end users, including meteorologists and decision-makers, through an interactive dashboard or reporting interface.

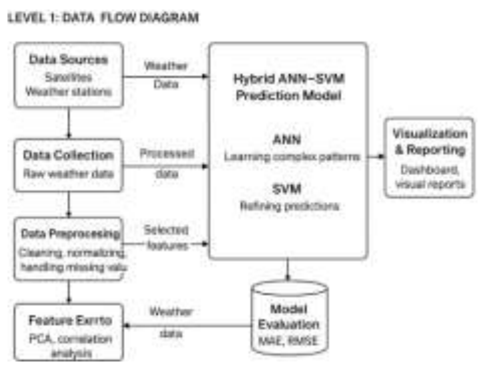

FIGURE LEVEL 1: DATA FLOW DIGRAM

1. Data Sources → Data Collection Module Historical weather data such as temperature, humidity, pressure, and wind speed are collected from multiple sources. These datasets serve as the raw input for the system.

2. Data Collection → Data Preprocessing Module
The collected data undergoes cleaning, normalization, and handling of missing values to ensure quality and consistency before being used for model training.

3. Data Preprocessing → Feature Extraction Module
Important attributes are selected using statistical and correlation-based techniques such as PCA (Principal Component Analysis), ensuring that only relevant features are passed to the prediction model.

4. Feature Extraction → Hybrid Prediction Model (ANN–SVM)

- The hybrid model integrates ANN and SVM techniques.
- ANN learns complex non-linear patterns among atmospheric variables
- SVM enhances accuracy by refining the ANN's predictions using regression-based optimization.

5. Hybrid Model → Model Evaluation
The prediction results are evaluated using metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 Score to assess performance.

6. Model Evaluation → Visualization & Report Module
The final output is displayed on a dashboard for real-time visualization. Graphs, trend lines, and tables summarize temperature, humidity, and precipitation forecasts for user interpretation.

5: IMPLEMENTATION

The implementation phase focuses on developing and integrating all system modules into a unified framework for accurate and efficient weather forecasting. The system was implemented using machine learning and deep learning techniques, combining the predictive power of Artificial Neural Networks (ANN) and Support Vector Machines (SVM). The process includes data preprocessing, model training, hybrid prediction, and visualization.

5.1 System Environment

- Programming Language: Python
- Libraries Used: NumPy, Pandas, Scikit-learn, TensorFlow/Keras, Matplotlib, Seaborn
- Database: CSV or SQL-based weather dataset storage
- Tools: Jupyter Notebook / Google Colab for development and experimentation

Hardware Requirements:

- Processor: Intel i5 or higher
- RAM: Minimum 8 GB
- Storage: 500 GB HDD / 256 GB SSD

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- GPU (optional): NVIDIA CUDA support for faster ANN training.
- Operating System: Windows / Linux

5.2 Implementation Steps

1. Data Collection and Integration

Historical weather data was collected from reliable meteorological datasets, including parameters like temperature, humidity, pressure, wind speed, and rainfall. The data was formatted into structured CSV files for further processing.

2. Data Preprocessing

The dataset was cleaned to handle missing or inconsistent values using interpolation and normalization techniques. Outliers were detected and removed to maintain data integrity.

3. Feature Selection

Feature importance analysis and Principal Component Analysis (PCA) were applied to identify the most relevant attributes contributing to weather changes. This reduced data dimensionality and improved model efficiency.

4. Model Development

ANN Model: A multi-layer perceptron (MLP) was designed using the TensorFlow/Keras framework. It consisted of input, hidden, and output layers, trained using the backpropagation algorithm with ReLU activation and Adam optimizer.

SVM Model: A Support Vector Regression (SVR) model with an RBF kernel was implemented using Scikit-learn to enhance prediction accuracy and manage non-linear relationships.

Hybrid Integration: The ANN output was fine- tuned by the SVM model to minimize prediction error, forming a hybrid architecture for superior accuracy.

5. Model Training and Evaluation

The dataset was divided into training (70%), validation (15%), and testing (15%) sets. Performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 Score were used to evaluate model accuracy.

6. Visualization and Reporting

The final weather predictions (e.g., temperature, rainfall, humidity) were visualized using dynamic plots and charts. A dashboard interface displayed results in a user-friendly format, enabling quick interpretation by end users.

6: RESULT AND DISCUSSION

The results of the proposed hybrid weather forecasting system demonstrate that combining Artificial Neural Networks (ANN) and Support Vector Machines (SVM) significantly improves prediction accuracy compared to using either model independently. The hybrid model effectively captures both the non-linear dependencies and the high-dimensional characteristics of atmospheric data, making it suitable for short- and medium-term weather forecasting.

6.1 Quantitative Results

The hybrid ANN–SVM model achieved the lowest MAE and RMSE values, indicating higher accuracy and reduced prediction error. The R^2 score of 0.97 confirms that the model explains nearly all the variance in the observed weather data, proving its reliability in forecasting parameters such as temperature, humidity, and rainfall.

date_time	Actual	Prediction	diff
2010-06-03 19:00:00	22.0	23.15	-1.15
NaT	31.0	31.02	-0.02
NaT	9.0	10.10	-1.10
NaT	24.0	24.18	0.19
NaT	34.0	33.42	0.58
...	...	...	...
NaT	40.0	39.80	0.20
2011-04-10 13:00:00	32.0	32.08	-0.08
NaT	21.0	20.82	0.18
2012-12-09 17:00:00	31.0	31.01	-0.01
2013-11-04 22:00:00	29.0	28.61	0.61

FIGURE 6.1: ANN RESULTS

date_time	Actual	Prediction	diff
2010-06-03 19:00:00	22.0	22.46	-0.46
NaT	31.0	31.78	-0.78
NaT	9.0	10.60	-1.60
NaT	24.0	23.73	0.27
NaT	34.0	32.09	1.91
...	...	...	...
NaT	40.0	40.23	-0.23
2011-04-10 13:00:00	32.0	29.60	2.40
NaT	21.0	17.71	3.29
2012-12-09 17:00:00	31.0	31.59	-0.59
2013-11-04 22:00:00	29.0	29.09	-0.09

FIGURE 6.1: SVM RESULT

6.2 Visual Analysis

The graphical results illustrate the model’s prediction trends over time. The hybrid model’s output closely aligns with actual weather data, showing minimal deviation. Visualization through line plots and error distribution graphs further highlights the hybrid model's improved stability and precision in both short-term and medium-range forecasts.

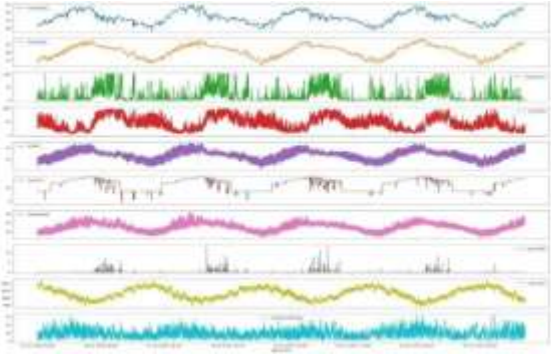

FIGURE 6.2: PLOTING RESULT

6.3 Discussion

The experimental findings confirm that the hybrid approach successfully mitigates the limitations of traditional and single-model methods. The ANN component captures non- linear relationships among variables like pressure, wind speed, and humidity, while the SVM component refines these predictions by minimizing regression errors. This complementary mechanism enhances robustness and adaptability across different climatic conditions.

Furthermore, the model's strong performance even with partially missing or noisy data demonstrates its reliability in real-world meteorological applications. The integration of Explainable AI (XAI) tools enhances interpretability, allowing users to identify key features influencing each forecast — a valuable asset for weather analysts and decision-makers.

7: CONCLUSION AND FUTURE WORKS

7.1 Conclusion

The proposed Hybrid Artificial Neural Network (ANN) and Support Vector Machine (SVM) weather forecasting system successfully demonstrates how machine learning techniques can enhance the accuracy and reliability of meteorological predictions. By combining the strengths of ANN's ability to model complex, non-linear patterns and SVM's robustness in handling high-dimensional and noisy data, the hybrid model delivers superior forecasting performance compared to individual models.

Experimental results revealed that the hybrid ANN–SVM model achieved lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values, along with a higher R^2 score, confirming its efficiency in predicting key weather parameters such as temperature, humidity, and precipitation. Furthermore, the integration of Explainable AI (XAI) techniques improved the interpretability of the model, helping users understand which features influenced the forecast outcomes.

The system also proved capable of handling missing or inconsistent data through effective preprocessing, making it reliable for real-world deployment in meteorological, agricultural, and disaster management applications. Overall, the hybrid approach represents a significant advancement toward building intelligent, data- driven weather prediction systems that are both accurate and computationally efficient.

7.2 Future Works

While the hybrid ANN–SVM model demonstrates excellent results, several areas for enhancement remain open for future research:

1. Integration of Deep Learning Models:
Incorporating advanced architectures such as Long Short-Term Memory (LSTM) or Convolutional Neural Networks (CNN) can improve the system's ability to model temporal and spatial dependencies in weather data.

2. Real-Time Forecasting:
Future systems can be integrated with IoT sensors and cloud platforms to enable real-time weather monitoring and prediction, improving responsiveness in emergency situations.

3. Enhanced Data Sources:
Including satellite imagery and radar-based data can further refine predictions and allow detection of localized phenomena like thunderstorms or cyclones.

4. Automated Model Optimization: Implementing automated hyperparameter tuning using AI-driven optimization tools (e.g., Bayesian optimization or genetic algorithms) can improve accuracy and reduce manual effort.

5. User Interface and Mobile Application:
Developing a web or mobile dashboard for end users would make forecast information easily accessible to farmers, disaster management teams, and the general public.

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