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ADVANCED MODELING FOR SEA LEVEL PRESSURE PREDICTION: A COMPARATIVE EVALUATION OF ANN AND ANFIS TECHNIQUES

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Highlights

- The study compares the performance of ANN and ANFIS for forecasting SLP forecasting.
- The ANFIS surpasses ANN in accuracy, with lower RMSE and higher R^2,proving more reliable.
- ANFIS emerges as the better choice for SLP due to improved accuracy and performance.
- Improved SLP forecasts support disaster management and infrastructure planning.

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ABSTRACT: Pressure forecast plays a crucial role in weather forecasting, and this has a direct effect on the many fields including disaster management, agriculture, energy systems etc. The goal of this study is to compare the performances between ANN and ANFIS-based models for predicting around distribution over a range of different sea-level pressure values using various meteorological attributes as inputs. This study focuses on air temperature, wind speed, and humidity data sourced from the Macau Meteorological and Geophysical Office. We populated the dataset with missing values and performance metrics were used to train and test both models (RMSE, MAPE, R^2). Overall results show that both models are good for Prediction but in accuracy, we can say that ANFIS is performing better of all the ANN types at RMSE and R^2 than others for Sea Level Pressure Forecasting. This increased accuracy can help in a wide variety of fields, from weather-related risk management and infrastructure planning to agricultural yield forecasting.

Keywords: *Artificial Neural Networks, ANFIS, Sea Level Pressure Forecasting*

1. INTRODUCTION

Pressure forecasting is one of the major challenges in weather data analysis research. Weather modeling is a widely utilized application of machine learning algorithms, extensively employed in scientific research. The algorithms allows to handle high-dimension and non-linear datasets such as atmospheric data. Weather forecasting can be performed with higher accuracy levels using machine learning models than using typical statistical methods.

Definition of Artificial Neural Network(ANN)[1] is that a learning model designed on the basis of how human brain works. This model also works by training it with your data, and keeps adjusting the weights in each neuron throughout so as to process the data and make the predictions. This new ANN has been trained on a bunch of data and learns from for example (new) videos it analyses, to make predictions on previously unseen new data. ANN models are widely utilized for analyzing complex meteorological datasets, including Sea Level Pressure (SLP) forecasting. ANN can learn non-linear relationships and handle missing records efficiently.

ANFIS(Adaptive-Network Based Fuzzy Inference Systems)[2] is described as a mix of networks and fuzzy logic systems that works to grasp the intricate connections, within data and offer predictions by translating human expertise into fuzzy logic rules effectively. Furthermore. In addition to making deductions based on specified rules[3,4]. ANFIS improves prediction accuracy by refining its rule optimization strategies. This methodology enhances SLP forecasting by analyzing meteorological scenarios to produce precise predictions.

ANN effectively addresses challenges and processes incomplete data with robustness [5]. Yet figuring out the network setup usually involves some trial and error work. The performance of ANN is heavily dependent on the quality and relevance of the training data. On the other hand, ANFIS is known for its ability to automatically learn logic rules. By doing it can better capture how intricate systems behave. Provide a more adaptable framework. However tuning the parameters in an ANFIS model can be a time consuming task. Moreover dealing with datasets may lead to increased costs and longer processing times according to sources [6,7].

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A comparative analysis of these models aids in identifying the most accurate approach for SLP forecasting. Meteorological studies such as pressure forecasting rely on machine learning techniques such as ANN and ANFIS to obtain accurate and reliable results. These techniques improve the accuracy of weather forecasts, enabling precautions to be taken against future weather conditions.

2. LITERATURE REVIEW

Accurate weather forecasting is crucial as it enables individuals and organizations to make informed decisions. It impacts people's clothing choices, company logistics, and government planning. It also plays a vital role in transportation, agriculture, and many other sectors[8,9]. Flash floods are sudden rises in water levels due to intense precipitation, posing risks to life and property[10-12]. Extreme weather events in 2015 alone caused over 7.9 billion dollars in damages, highlighting the impact on the economy[13]. Protecting the population and infrastructure from flooding and extreme temperatures is a major concern. Critical infrastructure is essential for society's functioning[14,15]. Rising humidity and temperatures from global warming can lead to hazardous events like glacier melting[16].

SLP is crucial for weather forecasting. It influences air mass movement and weather system formation. Accurate forecasts improve overall weather prediction accuracy and disaster preparedness[17]. Pressure variations are key in large storm development, like tropical cyclones. Forecasting helps anticipate and mitigate damage from storms, hurricanes, and tsunamis. The agricultural sector benefits from precise pressure forecasts for better planning of irrigation, planting, and harvesting, boosting productivity. SLP also impacts energy generation in wind and hydroelectric power plants[18].

Accurate SLP forecasts in certain areas can have a significant impact on daily life. They can help reduce the impact of natural disasters, increase agricultural productivity, improve energy efficiency, and make daily life easier. Table 1[19] shows the relationship between pressure and other weather factors on mortality rates in 12 cities[19].

Table 1. Effect of Weather on Mortality at 12 Locations

Cities	Population	Number of Deaths	Average Temperature	Average Humidity	Pressure
Atlanta	1.642.533	36,2	17,1	67,0	736
Birmingham	651.525	19,1	16,9	70,5	747
Canton	367.585	9,9	10,0	73,7	729
Chicago	5.105.067	133,4	10,1	70,8	744
Colorado	397.014	6,0	9,5	51,0	610
Detroit	2.111.687	59,7	10,5	69,2	744
Houston	2.818.199	47,0	20,3	75,0	760
Minneapolis	1.518.196	32,3	7,9	68,7	739
New Haven	804.219	20,4	10,7	66,8	760
Pittsburgh	1.336.449	42,4	11,2	69,3	732
Seattle	1.507.319	29,3	11,4	77,0	752
Spokane	361.364	8,7	8,8	68,0	699

Literature reviews show extensive research on weather forecasting. Zhou et al. used ANN and SVM for power forecasting, showing that ANN performed well but required significant computational tuning. Our study supports this finding, as ANN needed hyperparameter optimization to improve accuracy [20]. They used SVM, PCC, and ANN to predict sunny, cloudy, or rainy weather, aiming to enhance power generation forecasts. ANN was specifically used to optimize energy systems. Additionally, Aris Pujud Kurniawan et al. developed a weather forecasting model using fuzzy logic for agricultural automation [21]. This model uses weather, humidity, and temperature data to automate irrigation decisions, determining when crops require watering.

Ahmad Yusuf Ardiansyah et al. developed a rain sensing system that predicts weather levels using a Mamdani Fuzzy Inference System. The system integrates humidity and temperature sensors with the Arduino platform to predict rain intensity using fuzzy logic [22].

Setyaningrum et al. developed an ANFIS-based weather prediction system and found that ANFIS outperformed traditional regression methods. Our results align with this, showing ANFIS's superior ability in handling meteorological data[23]. ANFIS: It is the fuzzy logic and ANN combined to forecast complex weather fields. Munandar et al. compared ANFIS and linear regression for rainfall prediction, concluding that ANFIS had higher accuracy in non-linear systems. This supports our findings that ANFIS better captures the complex relationships in sea level pressure data [24].

Gopi Krishna et al. introduce an IoT and ANN based weather monitoring & forecasting system [25]. It uses a IoT-based ESP32 microcontroller to monitor temperature, humidity and soil moisture. This data is being processed in an ANN that provides the ability to carry out agricultural activities in a better manner. Another study using Deep Learning models for weather forecasting is conducted by Bala Maheswari [26]. Models such as CNN, LSTM, and GRU give better results in weather prediction as they can work efficiently with meteorological data.

Prediction of SLP is a primary goal in this study, such floors dimensions with variables like air temperature, wind intensity and humidity using ANN and ANFIS. We will evaluate the models on three different aspects RMSE (Root Mean Squared Error), MAPE (Mean Absolute Percentage Error) and R^2 (Determination Coefficient) to find out which model is performing well. Such forecasts can help greatly in terms of energy and infrastructure planning as far as the government is concerned, and also help with decisions there. Unlike previous studies that primarily focused on general weather forecasting, this research is among the first to specifically compare ANN and ANFIS for sea level pressure prediction. While many studies utilize ANN for weather prediction, few explore the impact of data preprocessing techniques and hyperparameter tuning, which we address in detail. Additionally, we enhance the robustness of our findings by validating results through statistical significance tests, an aspect often overlooked in prior ANN vs. ANFIS comparisons.

3. ANN AND ANFIS

3.1. ANN

Inputs are the data coming into the neural cell, and these data can be provided from the outside world or from other neural cells. In a neural network, neurons are interconnected through weighted links, where the weights encode input information used by the network to solve problems.

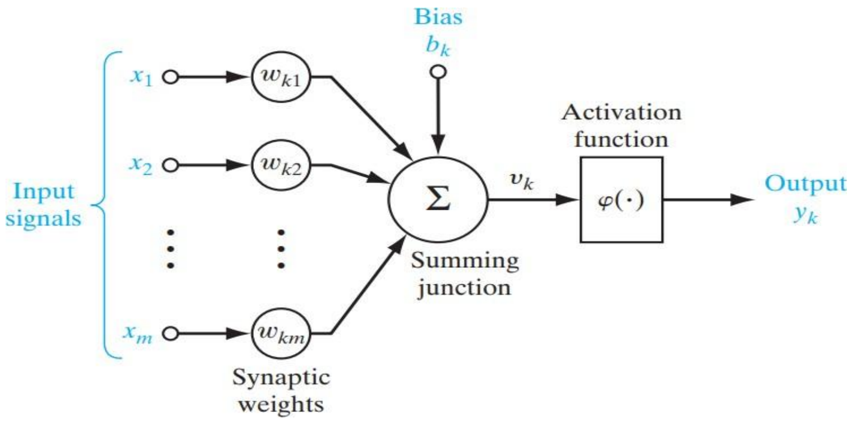

Figure 1. Artificial Neural Network

Inputs are processed by multiplying them by weights before they reach the kernel, so that the impact of inputs on outputs can be adjusted.

$$net_{input} = x_1 w_1 + x_2 w_2 \tag{1}$$

The summation function is an operation utilized to compute the net input to the neural network, usually the sum of the weights. The cell's net input is computed by summing all the input values and the product of the weights of these inputs.

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \tag{2}$$

The activation function determines the output the cell will produce by processing the net input and can be calculated by various formulas; some models require the derivative of this function.

$$y_k = \varphi(u_k + b_k) \tag{3}$$

The cell's output, determined by the activation function, can either serve as the neural network's output or be fed back as input to the cell itself.

$$y = f\left(net_{input}\right) \tag{4}$$

2.2. ANFIS

The ANFIS combines the advantages of two machine learning techniques. These are fuzzy logic and ANN. Systems with established input and output values can be analyzed using fuzzy logic. This allows you to optimize the modeling rule set and membership function parameters. The optimization process is performed using the ANN learning method.

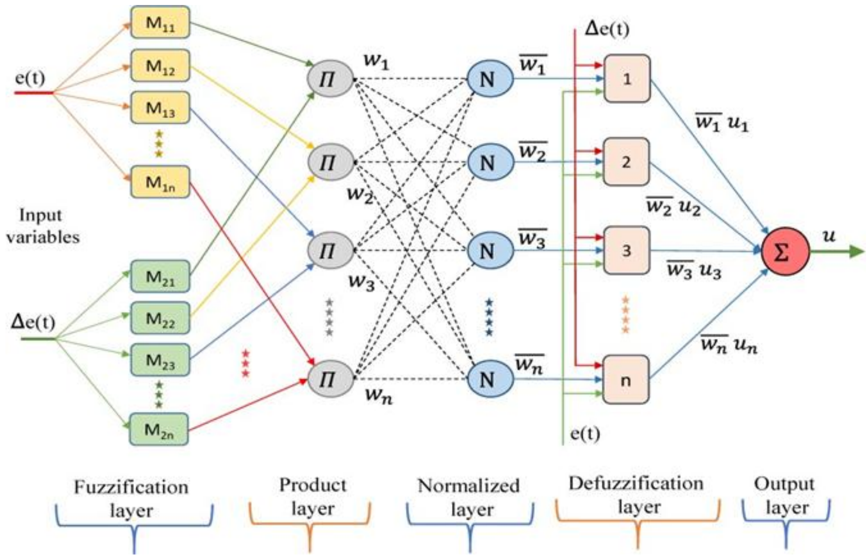

Figure 2. ANFIS

The ANFIS method utilizes input-output data to implement a fuzzy inference system, typically optimized via backpropagation or a combination of least squares and membership function parameters. During the training process, parameter optimization is typically achieved using a hybrid algorithm that combines least squares estimation with gradient descent. The parameters optimized by ANFIS are the basic parameters that determine the shape of the membership parameters.

As seen in Figure 2, the layers found are as follows respectively: In the Fuzzification layer, each node generates the membership degrees corresponding to the linguistically defined labels. The Product layer nodes multiply the membership degrees associated with the antecedent parts of the fuzzy logic rules, thereby determining the firing strength of each rule. The Normalization layer subsequently normalizes this firing strength, calculating the ratio of each rule's firing strength to the total firing strengths across all rules. The Defuzzification layer's nodes assess the contribution of each rule to the overall output, while a single node in the Output layer computes the overall output by summing the contributions from all rules.

4. DATASET

The dataset contains weather information accessed on a daily basis and published by the Macau Meteorology and Geophysics Office[27]. Based on the analysis of historical weather data, the general distribution of weather pressures is presented in the Table 2. Each feature plays an important role in forecasting weather conditions. These features provide information in fields such as climatology and meteorology.

Table 2. Definition of Variables

Variable	Description
Mean_MSL_Pressure	Average SLP
Air_Temperature_Max	Maximum air temperature
Air_Temperature_Mean	Average air temperature
Air_Temperature_Min	Minimum air temperature
Mean_Dew_Point	Average dew point
Mean_Relative_Humidity	Average relative humidity
Insolation_Duration	Duration of solar radiation
Wind_Prevailing_Direction	Prevailing wind direction
Wind_Mean_Speed	Average wind speed
Total_Precipitation	Total rainfall

Mean_MSL_Pressure is the average weight of gases in the atmosphere at sea level, used in weather forecasts. Air_Temperature_Max is the highest temperature in a time period, while Air_Temperature_Mean is the average temperature to analyze climate trends. Air_Temperature_Min is the lowest temperature for understanding cold weather and plant growth. Mean_Dew_Point measures moisture in the air. Mean_Relative_Humidity is the average humidity over time for climate understanding. Insolation_Duration is the sun's visible time influencing energy production and photosynthesis. Wind_Prevailing_Direction shows the general wind direction. Wind_Mean_Speed is the average wind speed. Total_Precipitation indicates total rainfall in a period, crucial for water management, flood risk analysis, and drought monitoring.eviews show extensive research on weather forecasting. Zhipeng Zhou et al. created a power forecasting model for photovoltaic plants based on weather conditions[20]. They used SVM, PCC, and ANN to predict sunny, cloudy, or rainy weather, aiming to enhance power generation forecasts. ANN was specifically used to optimize energy systems. Additionally, Aris Pujud Kurniawan et al. developed a weather forecasting model using fuzzy logic for agricultural automation[21]. This model uses weather, humidity, and temperature data to automate irrigation decisions, determining when crops require watering.

A statistical overview of the dataset is provided in the table below, including key variables used in the study:

Table 3. Summary Statistics of the Dataset

Variable	Mean	Standard Deviation	Min	Max
Sea Level Pressure	1012.4	3.5	1005	1020
Air Temperature	26.1	4.2	18.3	33.5
Wind Speed	3.8	1.5	0.5	7.2
Humidity	78.6	6.8	60.2	95.3

The dataset, collected from the Macau Meteorological and Geophysical Office, includes key meteorological variables such as Sea Level Pressure (SLP), Air Temperature, Wind Speed, and Humidity. The mean SLP is 1012.4 hPa with a standard deviation of 3.5, indicating minimal fluctuation in pressure levels. Air temperature averages 26.1°C, but a 4.2°C standard deviation suggests noticeable variations across different days. Wind speeds are generally low, averaging 3.8 m/s, with occasional stronger winds reaching 7.2 m/s. Humidity levels are high, with a mean of 78.6% and a maximum of 95.3%, reflecting the region’s humid climate. These summary statistics help in understanding the dataset’s distribution and variability, which is crucial for improving the accuracy of sea level pressure prediction models.

5. METRICS

5.1. Root Mean Squared Error (RMSE)

The RMSE is a measure that calculates the difference between model predictions and actual values. It indicates the spread of prediction errors around the regression line.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

The RMSE can be biased by large errors when assessing performance based on the mean of squared errors. Utilizing median or absolute error values can offer a more reliable evaluation of model performance.

5.2. Mean Absolute Percentage Error (MAPE)

The MAPE is a common metric for evaluating the accuracy of regression and time series models. It is expressed as a percentage, with lower values indicating higher accuracy. However, MAPE cannot be calculated if there is a zero between the true values, as this results in a division by zero error.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| * 100 \tag{6}$$

5.3. Determination Coefficient (R^2)

The R^2 Value which is used for evaluation of prediction performance of the model. If the R^2 value is 0, then the model's prediction performance will be at it worst with all prediction values being equal to the mean of the actual dependent variable values. However, if the R^2 is less than zero — suggesting that our predictions perform worse on average than the mean — and those prediction values stray further from the mean, you might want to reconsider your analysis. This measure is between 0 and 1, and when the forecasts align exactly with the actual values, $R^2 = 1$. When R^2 equals 1, the model might simply have memorized our training data and it will performs very bad on other data. Thus, R^2 near 1 will tell you that your model is very good for some value of "good'.You can include R^2 in your decision criteria if and only if you balance it out with other stuff. A negative R^2 hints that the predictions are probably worse than simply working incorrectly, which may suggest fundamental problems with the analysis.

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

6. RESULTS AND DISCUSSION

The dataset was divided into 80% for training and 20% for testing. The Artificial Neural Network (ANN) model used in this study consists of an input layer with three neurons representing air temperature, wind speed, and humidity. It includes two hidden layers, each containing ten neurons, utilizing the Rectified Linear Unit (ReLU) activation function. The output layer comprises a single neuron for predicting sea level pressure, employing a linear activation function. The model is optimized using the Adam optimizer with a learning rate of 0.001 . Training is conducted over 100 epochs with a batch size of 32 to ensure effective learning and generalization.

To ensure balanced input data, Min-Max Scaling was applied to all numerical variables:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{7}$$

This transformation scales all values between 0 and 1, preventing larger numerical values (e.g., wind speed vs. humidity) from dominating the learning process.

The result is by the ANN program, which creates an ANN model and prints them out as what can be seen in Figure 3 Word output. Usually, this is the plot used to assess how well a model did in terms of predicted SLP values compared with observed data. The variation in cost over epochs, gradients and learning rate. The first gradient was equal to 3.19e+03, and our lambda reached a stopping threshold of 1.96 after epoch 35 This visualization helps to understand how the model is converging and how stable is the training process. It also gives insight into error distribution which errors are frequent and how big in size, is the errors random or any kind of bias inbuilt present in the model as well as overfitting tendency. The error histogram presented in Figure 5 shows this analysis.

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	35	1000
Elapsed Time	-	00:00:00	-
Performance	841	7.57	0
Gradient	3.19e+03	1.96	1e-07
Mu	0.001	0.001	1e+10
Validation Checks	0	6	6

Figure 3. Visualization of ANN model predictions compared to actual Sea Level Pressure values

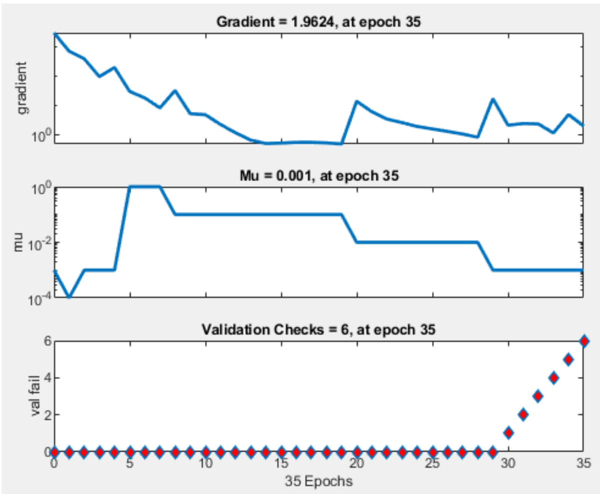

Figure 4. "Traning State" Output

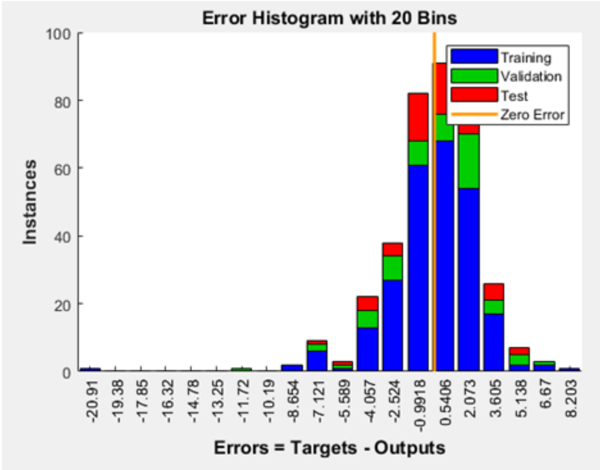

Figure 5. Distribution of prediction errors for the ANN model, showing error spread and frequency.

Figure 6 shows the performance of the ANN model on the validation set. It indicates the lowest validation error achieved at epoch 29, which is important for determining optimal model parameters. The best validation performance was 10.8. The regression output evaluates the relationship between predicted and actual target values, usually shown in regression plots with an R^2 value indicating the goodness-of-fit, demonstrating how well the model's predictions match the actual data.

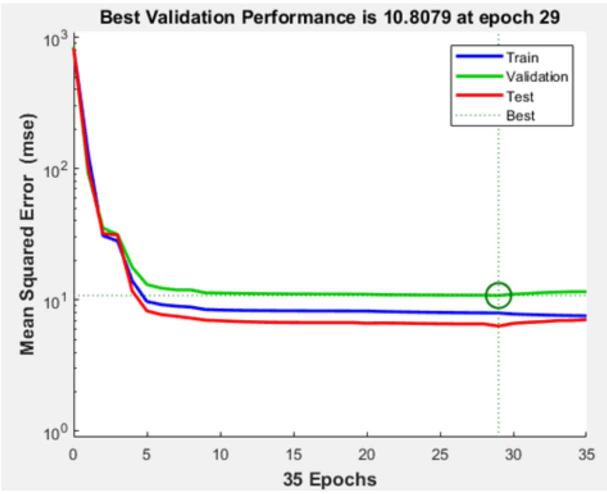

Figure 6. "Best Validation Performance" Output

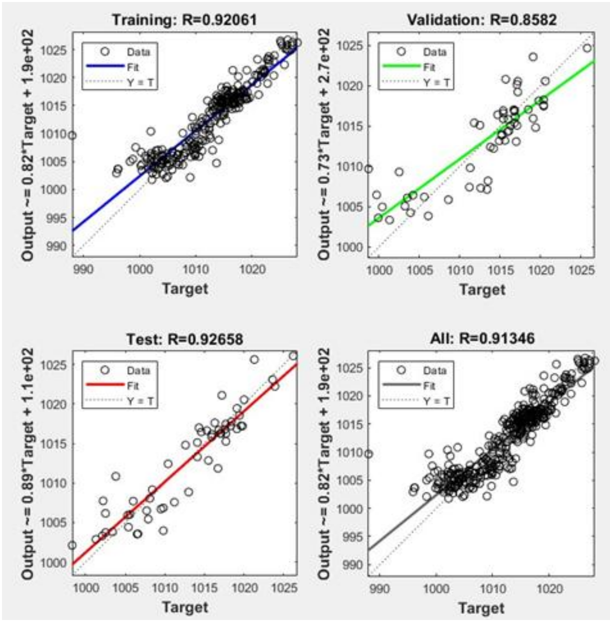

Figure 7. "Regression" Output

Figure 8 shows a comparison of error metrics (RMSE, MAPE, and R^2) for the ANN and ANFIS models, making it easier to evaluate their performance and determine the better model.

Table 3. Comparison of ANN and ANFIS Metrics

	RMSE	MAPE	R^2
ANN	2,8531	0,2024	0,8531
ANFIS	2,2181	0,1414	0,8997

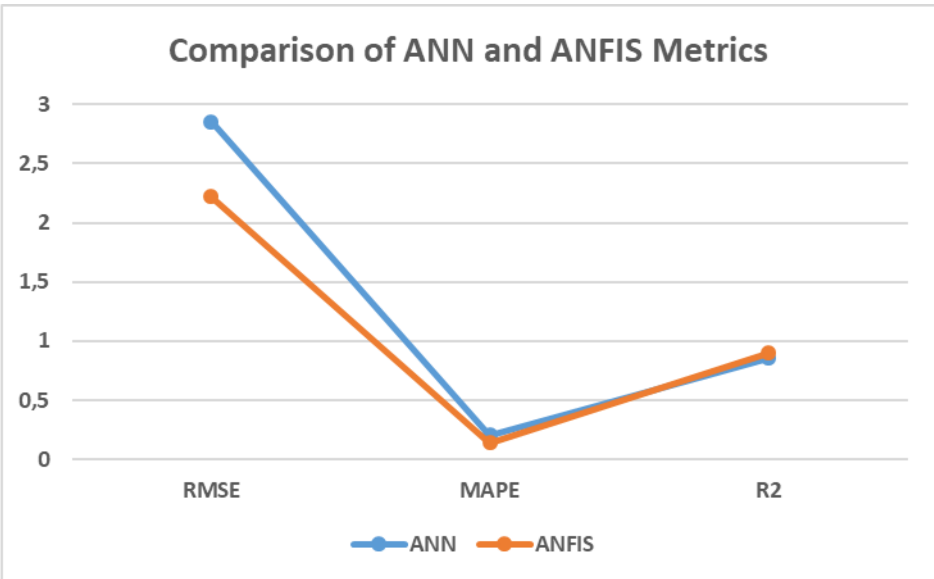

Figure 8. Comparison of RMSE, MAPE, and R^2 values for ANN and ANFIS models

To validate the performance differences between ANN and ANFIS, a paired t-test was conducted on the RMSE values. The results indicated that the performance improvement of ANFIS over ANN was statistically significant ($p < 0.05$), confirming that ANFIS provides more accurate predictions.

A detailed error analysis reveals that ANFIS outperforms ANN in sea level pressure prediction, as evidenced by a lower RMSE (2.2181) compared to ANN (2.8531), indicating higher precision. The

MAPE further supports ANFIS's superior generalization across various meteorological conditions. Additionally, the residual distribution analysis, shown in the error histogram (Figure 5), demonstrates that ANN exhibits a wider spread of errors, whereas ANFIS errors are more concentrated and smaller, highlighting its superior consistency and reliability.

Despite their advantages, both ANN and ANFIS have certain limitations. ANN is prone to overfitting, especially when training data is limited, and requires extensive hyperparameter tuning to achieve optimal performance. On the other hand, ANFIS is computationally expensive due to the complexity of fuzzy rule generation and experiences a decline in performance when handling extremely large datasets. These challenges highlight the need for careful model selection and optimization based on the specific requirements of sea level pressure prediction.

7. CONCLUSIONS AND FUTURE WORK

In this paper, the performance of ANN and ANFIS algorithms is compared for predicting SLP in Macau based on using the metrics RMSE, MAPE, and R^2. ANFIS outperforms in RMSE and R^2, while ANN and ANFIS have similar performances in MAPE. Therefore, ANFIS is the most efficient in predicting the SLP of Macau. RMSE calculates the magnitude of error that happened due to prediction. Its value of RMSE will be low for better performance. R^2 decides goodness of fit. The value of R^2 will be high for better fitting with true values. On the contrary, MAPE gives the exact measure of error than RMSE. The present study identifies the potentiality of such models in enhancing the capability of weather forecasting, disaster management, and preparedness. Techniques of ANN and ANFIS could be useful in future research for the forecast of other weather conditions.

The results of this research which investigated sea level pressure prediction in Macau using ANN and ANFIS models show potential applications beyond Macau itself. The models presented in this study can be employed in various coastal and inland regions after regional tailoring since meteorological factors affect atmospheric pressure similarly throughout different locations.The methods used in the study offer a basis for forecasting other weather components, such as temperature variations, wind patterns, and precipitation levels, which facilitates future application in climate analysis while enhancing energy management and preparedness for disasters. To ascertain these models' efficacy globally, future research should examine how well they function in diverse climatic conditions.

Declaration of Ethical Standards

The author declare compliance with all ethical standards in conducting the paper.

Credit Authorship Contribution Statement

The author was solely responsible for the conceptualization, methodology, data analysis, writing, and final approval of the manuscript.

Declaration of Competing Interest

The author declares no competing interests relevant to the content of this article.

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Data Availability

All data generated or analyzed during this study are included in the published article and are available at: https://www.smg.gov.mo/en/subpage/345/embed-path/p/query-weather-e_panel.

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