Jurnal Algoritma, Logika dan Komputasi *Vol.VIII (No. 02) : 799 - 809. Th. 2025*
Versi Online: https://journal.ubm.ac.id/index.php/alu *p-ISSN: 2620-620X*
DOI: http://dx.doi.org/10.30813/j-alu.v2i2.8782 *e-ISSN: 2621-9840*

PREDICTION OF EXPORT VOLUME IN SOUTH SULAWESI USING BPNN

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Diterima 10 Juli 2025 / Disetujui 21 Juli 2025

ABSTRACT

This study aims to develop a prediction model for South Sulawesi's export volume based on destination countries using the Backpropagation Neural Network (BPNN) method. South Sulawesi plays a significant role in the export of agricultural, marine, and mining commodities. Major constraints in the export process include unpreparedness of goods, limited commodity stocks, and a mismatch between production capacity and destination market demand. The export data used ranges from 2018 to 2024, with a total of 1,555 rows of data. The BPNN model with a 6-10-6-1 architecture was applied to recognize historical patterns and generate predictions. The test results showed a Mean Squared Error (MSE) value of 0.0161440, indicating high accuracy. Exports peaked at nearly 40 tons in 2019 and declined sharply in 2023, but are predicted to recover steadily in 2025–2026. The main destination countries include China, Japan, and East and Southeast Asian countries. The leading commodities are octopus, processed wood, and marine products. These findings demonstrate that the BPNN method is effective in predictive modeling for trade planning as well as the importance of logistics readiness and market diversification in maintaining export desires.
Keywords: *Backpropagation Neural Network, Export Volume, Commodity, Country, Prediction*

ABSTRAK

Penelitian ini bertujuan untuk membangun model prediksi jumlah ekspor di Sulawesi Selatan berdasarkan negara tujuan menggunakan metode Backpropagation Neural Network (BPNN). Sulawesi Selatan berperan besar dalam ekspor komoditas pertanian, kelautan, dan pertambangan. Kendala utama dalam proses ekspor meliputi adalah ketidaksiapan barang, keterbatasan stok komoditas, serta ketidaksesuaian antara kapasitas produksi dan permintaan pasar tujuan. Data ekspor yang digunakan berasal dari tahun 2018 hingga 2024 dengan total 1.555 baris data. Model BPNN dengan arsitektur 6-10-6-1 diterapkan untuk mengenali pola historis dan mmenghasilkan prediksi. Hasil pengujian menunjukkan nilai Mean Squared Error (MSE) sebesar 0,0161440, yang menunjukkan akurasi tinggi. Ekspor mencapai puncak hampir 40 ton pada tahun 2019 dan menurun tajam pada tahun 2023, namun prediksi pulih secara stabil pada 2025–2026. Negara tujuan utama meliputi Tiongkok, Jepang, dan negara-negara Asia Timur dan Tenggara. Komoditas unggulan adalah gurita, kayu olahan, dan produk kelautan. Temuan ini menunjukkan bahwa metode BPNN efektif dalam pemodelan prediktif untuk perencanaan perdagangan serta menegaskan pentingnya kesiapan logistik dan diversifikasi pasar dalam menjaga keberlanjutan ekspor.
Kata Kunci: Backpropagation Neural Network, Jumlah Ekspor ,Komoditas, Prediksi

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INTRODUCTION

South Sulawesi is one of the provinces in Indonesia that has a strategic role in international trade, especially in the export of agricultural products, fisheries, mining, and other commodities[1]. Several superior commodities such as seaweed, cocoa, and fishery exports are exported to various destination countries such as China, the United States, and Japan[2]. Based on data from the South Sulawesi Central Statistics Agency, the number of exports in South Sulawesi in 2024 reached 2,013.02 tons, a decrease of 15.23% compared to 2023 which reached 2,374.65 tons[3]. This decrease occurred due to several factors, including changes in global demand, the rupiah exchange rate, and the political and economic conditions of trading partner countries[4][5].

Export instability is influenced by internal factors, particularly those related to the readiness of goods to be exported[6]. One of the obstacles faced is the limited availability of export commodity stocks due to a mismatch between production capacity and demand in destination countries[7]. Unpreparedness in meeting export demand can result in trade opportunities not being optimally utilized[8]. This condition is exacerbated by the lack of a logistics planning system and This study aims to build a prediction model for the number of South Sulawesi exports based on destination countries using the BPNN method. The results are expected to support the development of academic research and become a reference in the formulation of data-based international trade policies, as well as strengthen regional economic planning that is adaptive to the global dynamics of prediction-based distribution, so that adjustments to spikes or decreases in demand cannot be made in a timely manner[9][10]. Therefore, a predictive approach is needed that is able to project export needs and demands accurately, so that supplies and distribution can be planned optimally to support the smooth flow of foreign trade[11][12]. Although prediction methods have been widely used in various fields, until now no model has been found that is specifically and optimally applied to the case of South Sulawesi exports by considering factors of the export destination country and relevant internal variables such as commodity availability and logistics readiness[13].

One relevant approach in facing this challenge is an artificial intelligence-based prediction method, specifically Backpropagation Neural Network (BPNN)[14]. This method has the ability to identify hidden data patterns in non-linear and multivariable data, and is able to carry out a learning process from historical data to produce accurate predictions[15]. BPNN has been used effectively in various research contexts, one of which is to predict the number of jewelry exports based on the destination country with a high level of accuracy, using a 3-12-1 network architecture and a Mean Squared Error (MSE) value of 0.033[16]. In addition, the accuracy of BPNN has also been proven in predicting daily rainfall at the BMKG Citeko station, producing very high accuracy, reaching 95.36%, with a precision value of 95.40%, and an F-measure of 92.00% [17]. The advantage of BPNN over other methods lies in its ability to recognize complex and non-linear data patterns more accurately than traditional predictive methods such as linear regression or ARIMA[18]. The effectiveness of BPNN in multivariate data prediction modeling also shows its empirical performance in handling real-world data across various fields, as well as its strong capability in prediction-based data modeling[19]. However, the application of BPNN to model and predict South Sulawesi's specific export volumes based on destination countries, taking into account logistical challenges and available commodity stocks, has not been widely explored in previous literature. Therefore, this study offers a novel approach by developing a predictive model that not only considers external dimensions (destination countries) but also integrates internal factors influencing regional export success. This model is expected to provide more contextual, accurate, and applicable projections for formulating data-driven trade strategies.

Based on these problems, this study formulates two main questions, namely how can a prediction model for the number of South Sulawesi commodity exports based on the destination country be built and tested using the Backpropagation Neural Network (BPNN) method? and how can the Mean Squared Error (MSE) value analysis be used to evaluate the performance of the BPNN model in predicting the number of exports based on the destination country? This study aims to build a BPNN-based export prediction model that is able to process historical data and produce more accurate projections of the number of exports based on the destination country. The expected benefits of this study are to contribute to the development of academic studies in the field of international trade prediction, become a reference for policy makers in formulating data-based export strategies, and strengthen regional economic planning that is adaptive to global dynamics.

METODE PENELITIAN

This study utilized export data sourced from the South Sulawesi Provincial Department of Industry and Trade. The data relates to export activity from South Sulawesi to various destination countries. A total of 1,555 rows of data were collected from the years 2018 to 2024, each containing six attributes: Month, Year, Destination Country, Commodity, Export Value (US$), and Export Quantity (Tons). The variable targeted for prediction in this study is Export Quantity (Tons) , which describes the total export volume of a commodity in units of weight to the destination country during a specific period. Meanwhile, five other variables serve as independent variables used in the predictive modeling and analysis process. Descriptive details regarding data characteristics can be seen in Table 1.

Tabel 1. Export Dataset

Month	Year	Country of destination	Commodity	Export Value ($)	Export Amount (Tons)
January	2018	South Africa	Fresh Sea Fish	19500	26
February	2018	United States of America	Coffee beans	5112507.02	842.7
March	2018	United States of America	Carrageenan	1731466.85	443.01545
April	2018	United States of America	Crab Meat	11841925.9	423.6279
May	2018	United States of America	Octopus	9170627.32	1450.09969
June	2018	United States of America	Fresh Sea Fish	902287.48	133.84366
July	2018	United States of America	Ikan Olahan	6461777.51	642.02764
August	2018	United States of America	Cocoa Butter	14335523.6	1323.2
September	2018	United States of America	Cocoa Cake	1140808.63	61.25
October	2018	United States of America	Cocoa Liquor	229512.8	40
November	2018	United States of America	Cocoa Powder	613642.84	239.25
December	2018	United States of America	Rubber	880366.4	564.48

After going through the pre-processing stage, the data is then used in the prediction process using the BPNN method. BPNN is an artificial neural network algorithm that is effective in modeling complex non-linear relationships between variables. This method works by constructing layers of interconnected neurons and learning from historical data through a backpropagation mechanism to minimize prediction errors.

The BPNN network modeling structure is designed to gradually learn complex input and output variables. Through an iterative training process, the network learns to recognize historical patterns, correct errors, and continuously update internal weights to improve prediction accuracy. The more complex and deeper the network architecture used and the higher the number of training iterations or epochs, the greater the model's ability to form non-linear representations of the training data. The BPNN network architecture used consists of three main layers: the input layer, the hidden layer, and the output layer. The BPNN network architecture is as shown in Figure 1.

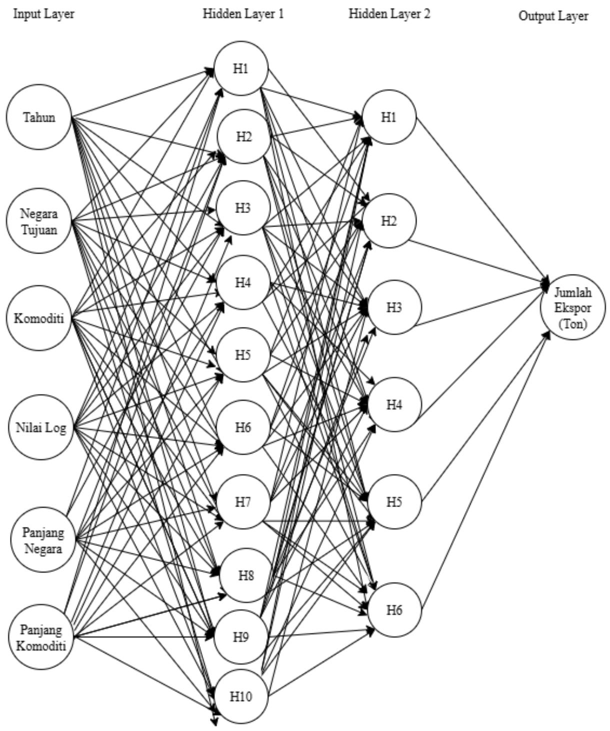

Figure 1. BPNN Model Architectur

In this network architecture, the input layer consists of six neurons representing each independent variable, namely Year, Destination Country, Commodity, Logarithmic Value (US$), as well as two additional features in the form of Country Length and Commodity Length encoded results. Each input neuron is fully connected to six hidden layer neurons. Each neuron in the hidden layer will calculate the total input value by summing the results of the multiplication between the weights and inputs, plus bias, as formulated in equation (1):

$$z_j = \sum_{i=1}^{n} w_{ij} x_i + b_j \tag{1}$$

Information:

z_j : input to neuron j

x_i : input from the previous neuron

Vol.VIII (No. 02) : 799 - 809. Th. 2025
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e-ISSN: 2621-9840

w_{ij} : weight between neurons *i* and *j*

b_j : bias neuron *j*

n : number of neurons in the previous layer

f : activation function, generally includes the sigmoid in equation 2:

$$f(z_j) = \frac{1}{1 + e^{-z_j}} \tag{2}$$

After the predicted value is obtained, the error calculation is carried out using the *Mean Squared Error* (MSE) function as shown in equation (3):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

With:

n : total number of data

y_i : actual value at the ith observation

$\hat{y}_i$: predicted value at observation i

Once the error value is known, the process continues to the backward propagation stage, where the network calculates the contribution of each weight to the total error generated. The local error on the output neuron is calculated using equation (4):

$$\Delta_k = (y_k - \widehat{y_k}) \cdot f'(z_j) \tag{4}$$

Information:

Δ_k : local error at the kth output *neuron*

y_k : target value of the kth *output*

$\widehat{y_k}$: actual output of the network

$f'(z_j)$: derivative of the activation function used (sigmoid)

The error in the hidden layer is calculated to determine its contribution to the final error. This calculation is carried out using equation (5):

$$\Delta_j = f'(z_j) \cdot \sum_k \Delta_k w_{jk} \tag{5}$$

Information:

Δ_j : local error at the *j -th hidden neuron*

w_{jk} : weight from neuron *j* to output neuron *k*

$f'(z_j)$: derivative of the activation function on neuron *j*

The weight update is done with equation (6):

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \eta \cdot \Delta_j \cdot a_i \tag{6}$$

Information:

$w_{ij}^{(t+i)}$: weight from neuron *i* to neuron *j* at iteration *t*

$w_{ij}^{(t)}$: weights updated in the next iteration

n : learning rate

Δ_j : error value at neuron *j*

a_i : activation (output) of neuron *i* in the previous layer

The training process is repeated for several iterations until the MSE value converges or reaches a predetermined minimum limit[20] [21].

RESULT

This study aims to implement the Backpropagation Neural Network (BPNN) method in predicting export volume based on six main features, namely month, year, destination country, commodity, export value (in logarithmic form), country name length, and commodity name length. The BPNN model used has a 6-10-6-1 network architecture, consisting of 6 neurons in the input layer (including the coding result category), 10 neurons in the first hidden layer, 6 neurons in the second hidden layer, and 1 neuron in the output layer that represents the predicted export volume. The ReLU activation function is used in both hidden layers, while a linear function is applied to the output layer. The model is optimized using the Adam algorithm and equipped with an early stop scheme to prevent overfitting. The dataset used is divided into two parts, namely 80% for training and 20% as test data to emit the model's generalization ability to data that has never been seen before.

The BPNN model was used to predict export volumes over a six-month period from January 2018 to June 2026. In the historical period (2018–2024), the model showed a fairly accurate trend in following the actual trend. For example, the prediction for January 2018 reached 30.57 tons, close to the actual value of 28.66 tons. Other prediction results, such as those for June 2018, January 2023, and June 2024, also showed a good level of accuracy. For the future projection period, the model estimates export volumes of 19.87 tons in 2025 and an increase to 23.22 tons in 2026. This illustrates a stable growth trend, which can be used as a basis for strategic regional export planning.

Table 2. Predicted Export Amounts per 6-Month Period

Period	Current	Prediction
January 2018	28.66089964	30.5685595
Juni 2018	32.79534415	33.19357994
Januari 2019	39.26605378	32.93355041
Juni 2019	32.78267927	30.01583851
Januari 2023	28.45483893	25.40413418
Juni 2023	19.53513764	21.53753002
Januari 2024	21.61957349	24.22527241
Juni 2024	20.43954873	22.69636461
Januari 2025		19.86526121
Juni 2025		19.86526121
Januari 2026		23.2176094
June 2026		23.2176094

The BPNN model was then evaluated to determine its ability to recognize historical patterns and apply them to new data. The evaluation was performed by calculating the Mean Squared Error (MSE) on the training and test data.

Table 3. MSE Values Result

Dataset	MSE Values
Training data	0,0179364
Test data	0.0161440

The MSE value for the test data is 0.0161440, lower than the training data, which has an MSE value of 0.0179364. This indicates that the model does not experience overfitting and has good generalization capabilities. This means that the model not only learns from historical data but is also capable of making predictions with a low error rate on previously unused data. This reinforces the conclusion that the model is quite reliable and effective in predicting export volumes based on available data.

In addition, a feature importance analysis was also carried out using the permutation sensitivity approach, namely by randomizing each input feature and observing the resulting increase in MSE.

Table 4. Feature Importance

Feature	Influencing MSE Values
Export value	0,00082
Destination country	0,0047
Country name lenght	0,0026
Commodity name lenght	0,0018
Commodity	0,0009
Year	0,0006

These results show that export value (log) and destination country are the two features with the most significant influence on model performance. Conversely, the year feature, which is generally dominant in time series models, has the least influence. This indicates that the model relies more on structural data and market factors than simply following time patterns, and successfully captures the complexity of economic conditions and export market dynamics more accurately.

DISCUSSION

Historical Trend Analysis of Export Quantity Predictions

An analysis of historical export trends from 2018 to 2026 reflects global economic dynamics and the influence of external factors on export activity in South Sulawesi. Exports showed a significant increase, peaking at nearly 40 tons in mid-2019. However, this trend then gradually and sharply declined, reaching a low of around 19 tons in mid-2023. This decline was likely due to the impact of the pandemic and declining global demand. The BPNN model predictions indicate potential for a gradual recovery, with export volumes expected to stabilize around 23–24 tons in 2025–2026. This finding aligns with the results of the feature importance analysis, which indicates that time is not the primary factor, but rather market dynamics and destination countries are more important.

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Jurnal Algoritma, Logika dan Komputasi
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Vol.VIII (No. 02) : 799 - 809. Th. 2025
p-ISSN: 2620-620X
e-ISSN: 2621-9840

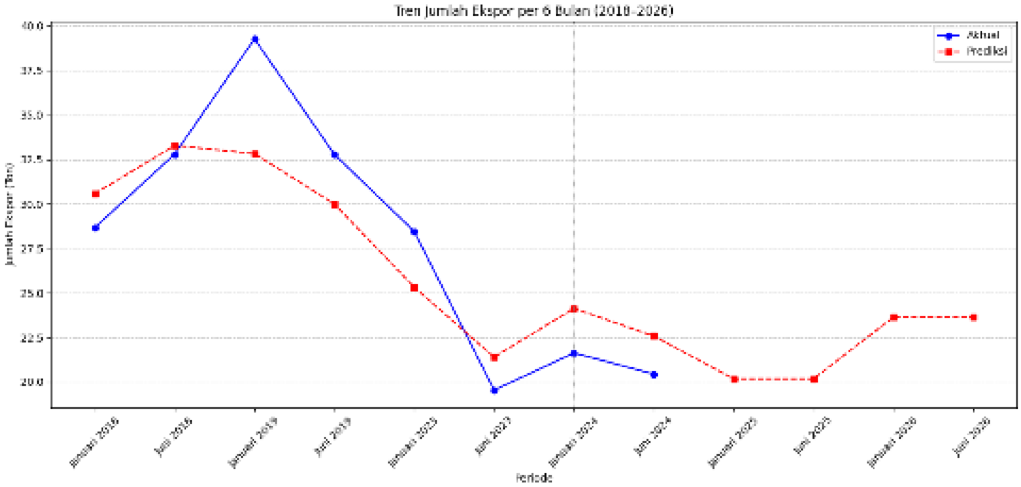

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Figure 2. Trend Graph of Export Amounts for the 6-Month Period

Impact of Destination Countries on Predicted Export Volumes for 2025-2026

Export destination countries play a crucial role in influencing export volumes, as market demand is highly dependent on key trading partner countries. Forecasts for the 2025–2026 period indicate that China remains the primary destination, with total exports of nearly 5,000 tons, followed by Japan, Malaysia, Australia, India, South Korea, and other countries in East and Southeast Asia. The concentration of exports in these regions reflects significant market potential while also indicating the risk of dependency. Therefore, market diversification is a crucial strategy to reduce vulnerability to changes in policy and global economic conditions.

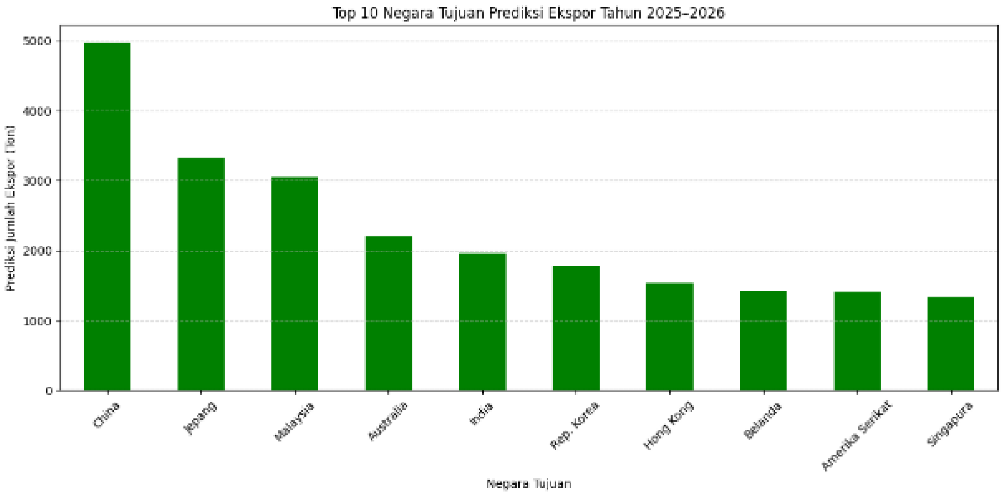

Figure 3. Predicted Export Volume Based on Destination Country for 2025-2026

Impact of Commodities on Export Volume Predictions

Commodity type also plays a role in determining the value and sustainability of regional exports. Predictions indicate that marine commodities such as octopus, processed wood, and carrageenan are the leading commodities dominating export volume, while agricultural commodities such as cloves, coffee beans, and peeled cashews continue to contribute, albeit on a smaller scale. This highlights the importance of strengthening the marine and fisheries sector through quality improvement, certification, and product downstreaming to sustainably enhance the competitiveness and added value of regional exports.

Vol.VIII (No. 02) : 799 - 809. Th. 2025
p-ISSN: 2620-620X
e-ISSN: 2621-9840

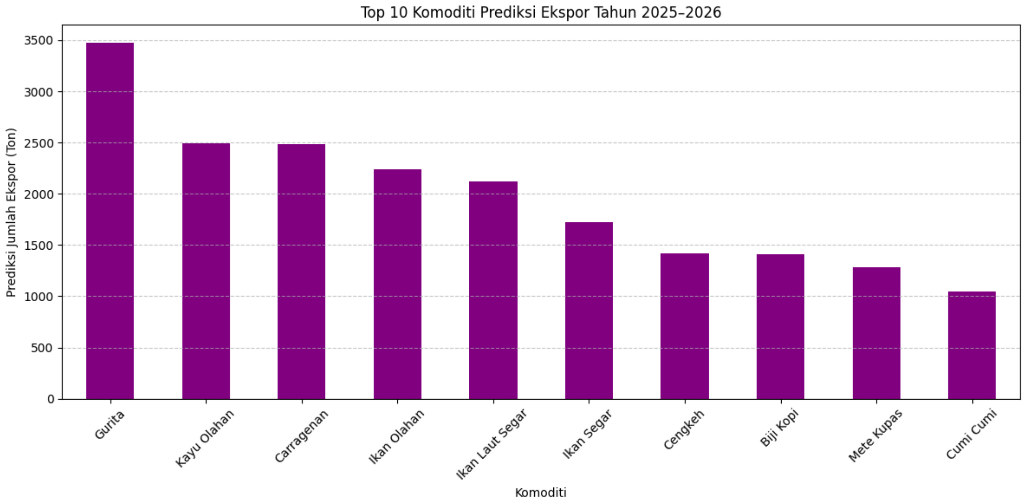

Figure 4. Predicted Export Volume by Commodity for 2025-2026

Comparison of this study with previous research

The BPNN model in this study demonstrated superior performance compared to several previous studies using a similar approach. The model performance evaluation results are shown through the Mean Squared Error (MSE) value on the test data.

Table 5. Comparison of MSE values from various studies

Research	Model	MSE Values
Hanum et al. (2022)	BPNN for jewerly export prediction	0,033
Siregar et al. (2021)	BPNN for coffee export predition	0,027
Utami & Darmawan	BPNN for predicting Indonesian CPO export	0,030

Hanum et al. (2022) used the BPNN method to predict the value of Indonesian jewelry exports and produced a Mean Squared Error (MSE) of 0.033. Meanwhile, Siregar et al. (2021) applied BPNN to predict coffee exports from North Sumatra to the United States, with a minimum wage (UMK) of 0.027. Furthermore, Utami and Darmawan (2020) predicted Indonesian palm oil (CPO) exports using the BPNN model and obtained an MSE of 0.030. These three studies generally focused on a single commodity and had a more limited geographic scope.

In contrast, this study developed a BPNN model with a 6-10-6-1 architecture designed to simultaneously predict the export value of various commodities to multiple destination countries. Furthermore, this model is supported by a series of important steps, including data preprocessing (normalization and coding), optimal parameter selection using GridSearchCV, and performance evaluation based on data testing and training. This strategy contributed to a higher level of satisfaction, as indicated by a lower MSE value of 0.0161. Thus, the approach used in this study proved to be more effective and has great potential as a tool for data-driven export planning.

CONCLUSION AND SUGGESTIONS

This study aims to implement the BPNN method in predicting export volumes in South Sulawesi based on destination countries using the BPNN method. The BPNN model with a 6-10-6-1 architecture used in this study is able to effectively learn historical patterns of export data. Model evaluation produced a *Mean Squared Error* (MSE) value of 0.0161440, indicating that the model has fairly good accuracy and strong generalization capabilities to previously unseen data. The model is able to follow actual trends in the historical period and projects a gradual recovery in exports in 2025-2026 in the range of 19.87 tons to 23.22 tons. This prediction indicates potential stability after the sharp decline in 2023. The dominance of exports to East and Southeast Asian countries, especially China, presents both opportunities and risks of market dependence, necessitating a diversification strategy. In addition, superior commodities such as octopus, processed wood, and marine products are the main pillars of exports, so exports need to be strengthened through quality improvement, certification, and product downstreaming to maintain regional export competitiveness.

Based on the research results on export volume prediction in South Sulawesi using the BPNN method, several suggestions can be given to improve the accuracy of future export predictions, including testing other machine learning methods such as Random Forest or LTSM as a comparison, improving the quality and completeness of export data, and establishing collaboration between researchers and export players and related trade agencies regarding the importance of strengthening data validity and developing data-based export policies. Strengthening the supply of superior commodities also requires improvements in distribution, certification, and downstreaming so that prediction results can be optimally utilized in regional export planning.

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Vol.VIII (No. 02) : 799 - 809. Th. 2025
p-ISSN: 2620-620X
e-ISSN: 2621-9840

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