JOURNAL OF
HYDRO-METEOROLOGY

Check for updates

Research Article

Spatiotemporal data analysis using deep learning models: A case study with drifting buoy data

Nguyen Gia Trong[1,2], Nguyen Xuan Hien[3], Vu Duc Manh[4], Tran Duc Vinh[5]*

[1] Hanoi University of Mining and Geology; nguyengiatrong@humg.edu.vn
[2] Geodesy and Environment research group, Hanoi University of Mining and Geology
[3] Vietnam Meteorological and Hydrological Administration; nguyenxuanhien79@gmail.com
[4] Hanoi University of Natural Resources and Environment; vdmanh@hunre.edu.vn
[5] Viet Nam's people naval hydrographic and oceanogtaphic department; vinhtduc@gmail.com

*Corresponding author: vinhtduc@gmail.com; Tel.: +84–984215679

Received: 5 October 2024; Accepted: 25 November 2024; Published: 25 March 2025

Abstract: Building or predicting the trajectory of drifting objects is significant in maritime studies and search and rescue operations. The trajectory of a drifting object can be determined using traditional tools with marine dynamic models or through artificial intelligence models. From the drifting buoy data collected between December 19 and December 28, 2003, the research team employed the CNN (Conv1D) model for analysis. The analysis results indicated that by using the Adam optimizer, the Huber loss function, and 256 filters in the hidden layer, the characteristic parameters for the model's performance were determined as RMSE = 0.04004, MAE = 0.032304 degrees, and R^2 = 98%. When using the SGD optimizer and the mean squared error (MSE) loss function, both RMSE and MAE values decreased by up to four times compared to the previous case, while the R^2 value reached 99.9% with 64 filters in the hidden layer. When the number of filters in the hidden layer was increased to 128, the performance of the CNN (Conv1D) model improved by up to 20%, with RMSE = 0.007863deg and MAE = 0.006653deg. The R^2 value when predicting the trajectory of drifting buoys using the CNN (Conv1D) model with the SGD optimizer and the MSE loss function approached approximately 100%, indicating that this model is suitable for the input data in predicting the trajectory of drifting buoys. Increasing the number of filters in the model's hidden layer from 128 to 256 did not change the model's predictive performance, demonstrating that the optimal number of filters for this case is 128. However, the RMSE result achieved in this study is still relatively large (0.87 km), possibly due to the limited input data. Future work should continue to experiment with drifting buoy data analysis using a larger input dataset.

Keywords: Drifting buoy data; Artificial intelligence; Deep learning; Time series data.

1. Introduction

To ensure maritime safety, it is essential to forecast the position of drifting objects at sea for search and rescue operations and to predict the trends influenced by environmental incidents, such as oil spills. Numerous studies have been conducted on predicting drifting objects at sea [1, 2]. To address the problem of predicting drifting objects at sea, one can utilize traditional mathematical models [3] or apply artificial intelligence models [4, 5].

The use of recurrent neural networks to improve the accuracy of drifting buoy trajectory models at sea, optimizing ocean surface flow data is explored in [6]. This model integrates data from drifting buoys and satellites to address the limitations of traditional models in predicting small flows, enhancing both temporal and spatial resolution. Experiments were conducted in the Gulf of Mexico. Acoustic depth measurement buoys attached to DFADs are employed in [7] to improve tropical tuna fishing efficiency. Using a random forest method, acoustic signals are analyzed to detect the presence and size of tuna schools, achieving a detection accuracy of 75-85% beneath DFADs in the Atlantic and Indian Oceans. These results contribute to creating an independent index of tuna quantities, aiding in conservation and resource management.

Statistical methods for predicting water current velocity (WC) based on the relationship between the position and velocity of drifting buoys have been proposed in [8]. Two methods were applied: weighted least squares regression for linear relationships and support vector regression for nonlinear spaces. The results showed a good agreement between actual measurements and WC predictions from field experiments near San Diego.

The potential of using Global Navigation Satellite Systems (GNSS) to measure river water levels has been explored through the development of compact and user-friendly buoys equipped with high-precision GNSS receivers. These buoys were tested in the Mekong Delta, Vietnam, where they produced highly accurate results, with a mean error of less than 2 cm. The buoys show promise for applications such as flood monitoring and tracking water movements, while also providing valuable data on hydraulic systems [9]. The FreeOceanWave Dataset (FOWD) was developed to analyze extreme wave events at sea, aiding in the conversion of raw data into clear categories of sea state parameters. With enough data on wave height, sharpness, and maximum wave height, this dataset enables strong predictions of extreme wave activity [10].

A machine learning method based on the Extra Trees (ET) algorithm was proposed to predict large wave heights in coastal areas. By utilizing data from CDIP buoys, this method achieved a Scatter Index of 0.130 and RMSE of 0.14 for one-day predictions, and a Scatter Index of 0.110 with an RMSE of 0.122 for 14-day predictions. These results show that the method outperforms existing prediction techniques [11]. Efforts were made to enhance the accuracy of particle tracking techniques near the Korean Strait by comparing flow-based tracking models with machine learning models. The data used included the movement trajectories of drifting buoys, predictions from linear regression and decision trees, as well as predictions from numerical models. The results indicated that the decision tree model achieved the highest accuracy in terms of CC and RMSE, while the MOHID model performed best in terms of NCLS [2].

Harmful algal blooms (HABs) pose significant threats to public health and aquatic ecosystems. A system combining high-frequency automated monitoring with machine learning techniques has been employed to develop soft sensors for chlorophyll-a (Chl-a) data. Over a three-year period, data from the As Conchas reservoir demonstrated that the Chl-a sensor provides a rapid and cost-effective method for water sampling in areas at risk [12]. A new framework based on novel data has been developed to accurately estimate the drift of objects in marine environments in real-time, combining awareness-based sensor technology and deep learning algorithms. The research established the drift characteristics of objects such as humanoid 3D models and rectangular pelican boxes, with wind and flow factors measured throughout the experiments. The results indicate that drift coefficients are significantly influenced by wind and flow [13].

A deep learning model integrating attention mechanisms with ResNet GRU (RGA) was proposed to predict the short-term drift of multifunctional buoys, with the goal of improving the accuracy of buoy location tracking. The experimental results demonstrated that RGA outperformed other models, achieving mean error, mean absolute error, and mean percentage error values of 5.11, 1.61, and 15.58, respectively [1]. A new machine learning framework for short-term wave condition prediction was proposed to aid in decision-making for maritime operations. By combining Long Short-Term Memory (LSTM) networks with existing spatial prediction models, the system achieved high accuracy, with R^2 values of 0.9083 for one-hour wave height predictions. These results showed that the model's performance was comparable to traditional prediction products [14].

A drift trajectory prediction technique was validated to reduce the impact of rising maritime incidents in South Korea. The findings showed that incorporating drift factors significantly enhances the accuracy of position predictions, which is essential for improving maritime search and rescue operations [15]. A long-term trajectory prediction solution for surface drifting buoys (SDB) based on artificial intelligence technology is proposed. The CNN–BiGRU–Attention model was developed to improve trajectory prediction accuracy, showcasing excellent convergence and generalization performance in SDB predictions under diverse marine conditions [5].

Numerical methods and monthly averaged data were applied to determine the trajectory of drifting objects at sea, providing initial guidance for their general drift direction [16]. The MIKE model was used to simulate the drift trajectories of objects in specific cases [17].

Artificial intelligence has been relatively widely used in research to determine the risk of natural disasters in spatial contexts [18, 19] or analyze time-varying data sequences [20, 21], with limited studies on analyzing data that changes both spatially and temporally, such as data from drifting buoys at sea. Vietnam has a maritime area of up to millions of square kilometers, playing a crucial role in ensuring territorial sovereignty, national security, and the socio-economic development. Forecasting the positions of drifting buoys specifically, and forecasting the trajectories of drifting objects in general, is crucial for search and rescue operations at sea. Additionally, the forecasting results contribute to the accurate interpolation of data used in oceanographic research, such as current data, sea surface temperature, salinity, etc. These data are all spatially and temporally dynamic. The CNN (Conv1D) model has proven effective in time series data prediction; hence, this study proposes applying the CNN (Conv1D) model to forecast the trajectory of drifting buoys using experimental data from the East Sea.

2. Materials and methodology

Drifting buoy data is provided by various scientific organizations worldwide, such as the National Oceanic and Atmospheric Administration (NOAA) [22], the European Space Agency (ESA) [23], etc. This study uses drifting buoy data provided by NOAA. The collected data can be stored in .csv format with a wealth of information, including the drifting buoy's ID, time, latitude, longitude, northward and eastward velocity, details about the buoy type, managing agency, and some other information. Some detailed information about the experimental data is provided in Table 1 below.

Table 1. Detailed information about the study data.

Type of information	Details
Drifting buoy ID	41167
Start time	2003-12-19
Stop time	2003-12-28
Latitude (minimum, maximum) (degrees)	21.21863, 22.30562
Longitude (minimum, maximum) (degrees)	119.23117, 119.99896
Buoy type	SVP
Float Diameter (cm)	30.5
Signal Decimation (hour)	1

The research method in this paper is illustrated in Figure 1. Based on the original dataset, key information such as time, latitude, and longitude is processed and used as input for the artificial intelligence model. The focus of the prediction in this example is the latitude of the drifting buoy. To ensure compatibility with the computer program, the data format must be adjusted, such as normalizing time values. The dataset is subsequently divided into training and testing subsets, following a 70%-30% split. The normalized input includes components like time, latitude, and longitude, with latitude values serving as the primary target for prediction.

The Convolutional Neural Network (CNN) with Conv1D layers is a deep learning model designed specifically for processing sequential or time-series data, using one-dimensional convolutions. Instead of analyzing 2D spatial data (as in images), Conv1D applies filters across one dimension, which makes it ideal for temporal data such as sensor readings, stock prices, and audio signals. The Conv1D layers slide a filter over the sequence, capturing local patterns and essential features that contribute to understanding trends and patterns in the data. Advantages of Conv1D CNNs include their ability to efficiently handle sequential dependencies by capturing important temporal features while requiring less computational power than traditional RNNs. Conv1D models also allow for effective parallelization during training, making them faster and more scalable for large datasets. Additionally, they offer flexibility in processing multivariate data, which can enhance predictive performance in time-series analysis tasks.

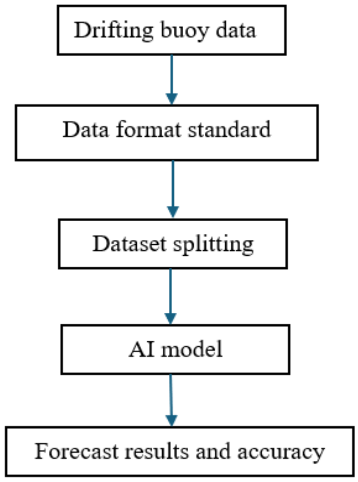


Figure 1. Method for predicting drifting buoy data at sea.

In this study, the CNN (Conv1D) model was constructed with 256 filters in the hidden layer. The Adam optimizer and Huber loss function were used, with the number of epochs set to 200 and batch size set to 16. When implementing artificial intelligence models, evaluating model performance is important to ensure reliability and accuracy. Some typical parameters commonly used for this purpose are as follows:

- Mean Squared Error (MSE): Measures the average squared difference between predicted and actual values, providing insight into model accuracy. Lower MSE values indicate a better fit.

- Root Mean Squared Error (RMSE): The square root of MSE, RMSE expresses error in the same units as the data, making interpretation easier. It's particularly useful for identifying larger prediction errors.

- Mean Absolute Error (MAE): Represents the average of absolute errors, showing how close predictions are to actual values without penalizing large errors more heavily than smaller ones, as MSE does.

- R-squared (R^2): Indicates the proportion of variance in the dependent variable explained by the model. An R^2 close to 1 suggests strong predictive accuracy.

- Cohen's Kappa: Measures the level of agreement between predicted and actual classifications, considering random chance. Higher Kappa values denote better agreement.

- F1-Score: Balances precision and recall, especially useful in classification tasks with imbalanced classes, by providing a single metric for both accuracy and coverage.

Based on the method selected above, the research team developed a data prediction program using the CNN(Conv1D) model with Python [24, 25], which incorporates library functions such as pandas, numpy, and sklearn [26, 27], among others.

3. Results and discussion

3.1. Prediction results with the CNN (Conv1D) model

With the research method and the computer program developed as presented in the previous section, the prediction results of the latitude component of the drifting buoy trajectory with the statistical parameters are shown in Table 2.

Table 2. The parameters characteristic of the forecasting performance of the CNN(Conv1D) model.

ID	MSE (deg)	RMSE (deg)	MAE (deg)	R^2	F1-Score	Kapa
41167	0.00160	0.04004	0.032304	0.9796	0.9667	0.9333

From the data in Table 2, it can be seen that although the CNN (Conv1D) model has been constructed very well with the input data (as indicated by an R-squared value of 97.96%), the values of RMSE and MAE are still very high. Figures 2a-2c represent the values of the loss function, the predicted values on the training dataset, and the predicted values on the testing dataset with the CNN (Conv1D) model.

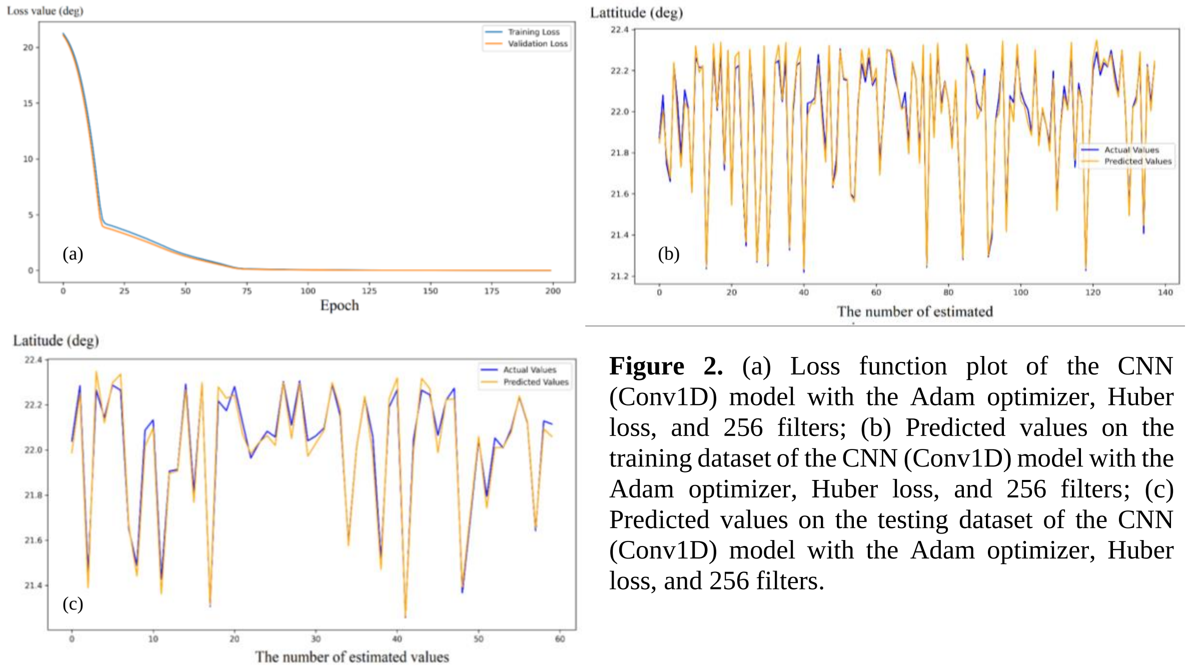


Figure 2. (a) Loss function plot of the CNN (Conv1D) model with the Adam optimizer, Huber loss, and 256 filters; (b) Predicted values on the training dataset of the CNN (Conv1D) model with the Adam optimizer, Huber loss, and 256 filters; (c) Predicted values on the testing dataset of the CNN (Conv1D) model with the Adam optimizer, Huber loss, and 256 filters.

3.2. Improving the Performance of the CNN (Conv1D) Model

With the above prediction results, the requirements for location prediction at sea have not been met. To improve forecasting performance, the Adam optimizer was replaced with the SGD optimizer, and the corresponding loss function was changed to MSE.

The Stochastic Gradient Descent (SGD) optimizer is a widely used algorithm for optimizing machine learning models, especially in neural networks. Unlike traditional gradient descent, which calculates gradients based on the entire dataset, SGD updates the model's parameters using only a single or a small batch of samples at each step. This approach makes SGD computationally efficient, particularly when dealing with large datasets, as it reduces memory usage and speeds up the learning process. Although SGD may lead to more fluctuations during training, it often helps the model to escape local minima and achieve better generalization. With a learning rate adjustment, SGD can be highly effective for training deep learning models across various domains, including image and language processing tasks.

The Mean Squared Error (MSE) loss function is a common metric for evaluating model performance in regression tasks. MSE calculates the average of the squared differences between predicted and actual values, emphasizing larger errors. This sensitivity to significant deviations makes MSE particularly useful for capturing the accuracy of continuous predictions. By penalizing larger errors more heavily, MSE encourages the model to produce closer estimates, making it a reliable choice in applications where precision is critical.

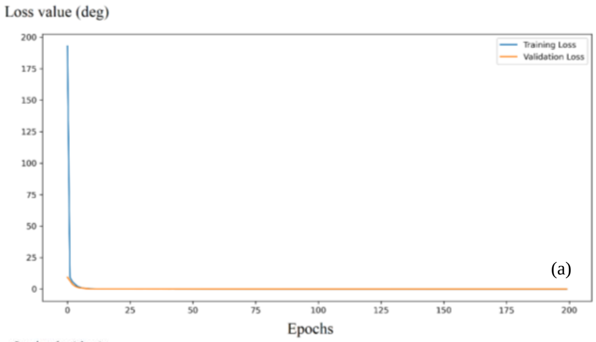
To investigate the performance of the CNN (Conv1D) model in this case, the number of filters used in the hidden layer was 64, 128, and 256, respectively. The performance statistics of the model are presented in Table 3.

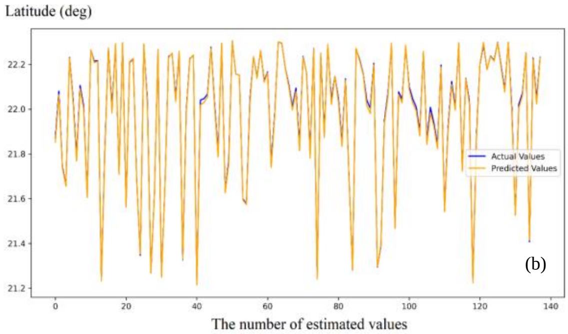
Table 3. Performance of the CNN (Conv1D) model with the SGD optimizer, MSE loss function, and different numbers of filters in the hidden layer.

Number of filters	MSE (deg)	RMSE (deg)	MAE (deg)	R^2	F1-Score	Kapa
64	0.000102	0.010090	0.007981	0.9987	1.0	1.0
128	0.000062	0.007863	0.006653	0.9992	1.0	1.0
256	0.000060	0.007745	0.006890	0.9992	1.0	1.0

From the data in Tables 2, 3, it can be seen that replacing the Adam optimizer with SGD and the Huber loss with MSE, using only 64 filters in the hidden layer, has improved the forecasting performance of the CNN (Conv1D) model. Accordingly, the RMSE value decreased by 4 times (from 0.04 to 0.01), and the MAE value similarly decreased by 4 times.

Figures 3a-3c represent the values of the loss function, the predicted values on the training dataset, and the predicted values on the testing dataset with the CNN (Conv1D) model in the case of using the SGD optimizer, MSE loss function, and 64 filters in the hidden layer.





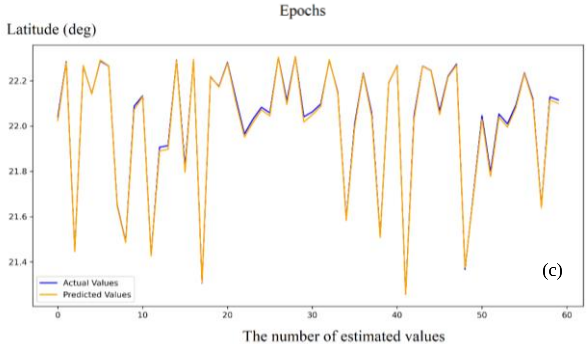


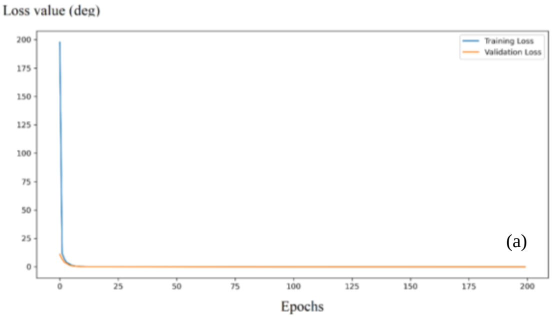
Figure 3. (a) Loss function of the CNN (Conv1D) model with the SGD optimizer, MSE loss function, and 64 filters in the hidden layer; (b) Predicted values on the training set of the CNN (Conv1D) model using the SGD function, MSE, and 64 filters in the hidden layer; (c) Predicted values on the training set of the CNN (Conv1D) model using the SGD function, MSE, and 64 filters in the hidden layer.

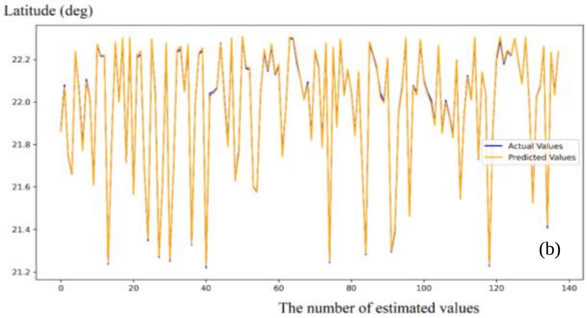
Figures 3a-3c show that, even with only 64 filters in the hidden layer, using the SGD optimizer and MSE loss function leads to a rapid decrease in loss toward zero (around 5 epochs compared to 75 epochs previously). Additionally, the CNN (Conv1D) model captures peaks more accurately when using the SGD and MSE functions, as reflected in the predicted values for both the training and testing datasets in Figures 3b, 3c.

When increasing the number of filters from 64 to 128 or 256, the model's fit to the input dataset remains the same. In all cases, the R-squared value is approximately 100%. However, when increasing the number of filters from 64 to 128 in the hidden layer, the RMSE value decreases by approximately 20%, and the MAE value decreases by approximately 15%.

When increasing the number of filters from 128 to 256 in the hidden layer, there is no significant change in the model's performance metrics. In other words, using the CNN (Conv1D) model with the SGD optimizer and MSE loss function in this case, the optimal number of filters in the hidden layer is 128.

The graphs showing the loss function values, predicted values on the training dataset, and predicted values on the testing dataset, using 128 filters in the hidden layer, are presented in Figures 4a-4c. Comparing the graphs for cases using 64 and 128 filters in the hidden layer shows that the loss function value remains nearly unchanged, but with 128 filters in the hidden layer, the predicted values align more closely with the actual values.





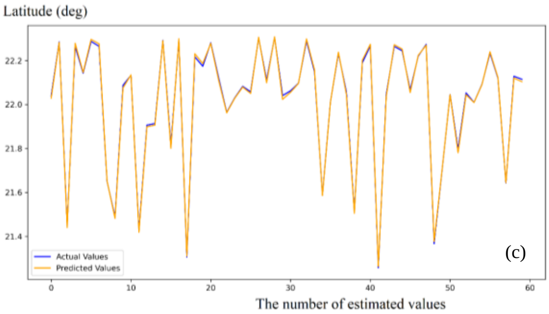


Figure 4. (a) Loss function of the CNN (Conv1D) model with the SGD optimizer, MSE loss function, and 128 filters in the hidden layer; (b) Predicted values on the training set of the CNN (Conv1D) model using the SGD function, MSE, and 128 filters in the hidden layer; (c) Predicted values on the testing set of the CNN (Conv1D) model using the SGD function, MSE, and 128 filters in the hidden layer.

From the above results, it can be observed that although the performance metrics of the model, such as R-squared, Kappa, and F1-Score, reach absolute values, the prediction accuracy is still not high, as indicated by the relatively large RMSE value. This may be due to the limited data and the significant spatial (geographical range) and temporal variations. Further research with a larger dataset is needed to fully assess the effectiveness of artificial intelligence models in analyzing drifting buoy data.

4. Conclusion

The results of this study indicate that predicting the trajectory of drifting buoys is significantly important for maritime traffic, scientific research at sea, and search and rescue operations. These studies are particularly relevant in Vietnam, a country with over 1 million square kilometers of sea, where the East Sea has strategic significance in ensuring territorial sovereignty and economic development.

Using the collected drifting buoy data, the research team developed a program to forecast the trajectory of drifting buoys utilizing the CNN (Conv1D) model. Experimental results show that by using the Adam optimizer, the Huber loss function, and 256 filters in the hidden layer, the forecasting performance achieved was RMSE = 0.04004 (degrees), MAE = 0.032304, and R^2 = 97.96%.

When the Adam optimizer was replaced with SGD, using the MSE loss function instead of the Huber loss function, just 64 filters in the hidden layer resulted in a forecasting performance four times higher, with statistical measures such as RMSE = 0.010090 (degrees) and MAE = 0.007981 (degrees). The fit between the model and the input data in this case was R^2 = 99.87%.

Continuing with the SGD optimizer and the MSE loss function, but increasing the number of filters in the hidden layer to 128, the model's performance increased by approximately 20%, yielding RMSE = 0.007863 (degrees), MAE = 0.006653 (degrees), and R^2 = 99.92%. When the number of filters was raised to 256, the model's performance did not change, indicating that the optimal number of filters in this experimental case is 128.

With R^2 values in all cases approaching 100%, this demonstrates that the proposed CNN (Conv1D) model is highly suitable for predicting the trajectory of drifting buoys that changes in both space and time. However, with the RMSE results still being relatively high, this may be due to the input data not being sufficiently large. Future research should continue to experiment with the predictive performance of artificial intelligence models using larger input datasets.

Author contributions: Conceptualization: N.G.T., N.X.H., V.D.M., T.D.V.; Methodology: N.G.T., N.X.H., N.D.V.; Data processing: N.G.T., N.D.V., N.X.M.; Writing - original draft: N.G.T., N.X.H.; Writing - review and editing: N.G.T., N.D.V.

Declaration: The authors collectively declare that this article is the result of their research, not previously published elsewhere, and not copied from previous studies; there is no conflict of interest among the authors.

References

1. Zeng, F.; Ou, H.; Wu, Q. Short-term drift prediction of multi-functional buoys in inland rivers based on deep learning. *Sensors* **2022**, *22(14)*, 5120.
2. Ha, S.Y.; Yoon, H.S.; Kim, Y.T. A study on the prediction of the surface drifter trajectories in the Korean Strait. *J. Korean Soc. Coastal Ocean Eng*. **2022**, *34(1)*, 11–18.
3. Spaulding, M.L.; Hewlett, E. Application of SARMAP to estimate probable search area for objects lost at sea. *Mar. Technol. Soc. J.* **1996**, *30(2*), 17–25.
4. Han, D.; Kim, Y.J.; Lee, S.; Lee, Y.; Kim, H.C. The estimation of arctic air temperature in summer based on Machine Learning approaches using IABP Buoy and AMSR2 satellite data. *Korean J. Remote Sens*. **2018**, *34(6_2)*,1261–1272.
5. Song, M.; Hu, W.; Liu, S.; Chen, S.; Fu, X.; Zhang, J.; Li, W.; Xu, Y. Developing an artificial intelligence-based method for predicting the trajectory of surface drifting buoys using a hybrid multi-layer neural network model. *J. Mar. Sci. Eng.* **2024**, *12(6)*, 958.
6. Aksamit, N.O.; Sapsis, T.P.; Haller, G. Machine-learning ocean dynamics from lagrangian drifter trajectories. *arXiv preprint arXiv* **2019**, 12895.
7. Baidai, Y.; Dagorn, L.; Amande, M.J.; Gaertner, D.; Capello, M. Machine learning for characterizing tropical tuna aggregations under drifting fish aggregating devices (DFADs) from commercial echosounder buoys data. *Fish. Res.* **2020**, *229*, 105613.
8. Diamant, R. Prediction of water current using a swarm of submerged drifters. *IEEE Sensors J.* **2020**, *20(19)*, 11598–11607.
9. Apel, H.; Hung, N.G.; Thoss, H.; Schöne, T. GPS buoys for stage monitoring of large rivers. *J. Hydrol.* **2012**, *412*, 182–192.
10. Häfner, D.; Gemmrich, J.; Jochum, M. FOWD: A free ocean wave dataset for data mining and machine learning. *J. Atmos. Ocean Sci.* **2021**, *38(7*), 1305–1322.
11. Pokhrel, P. Machine Learning in weakly nonlinear systems: A case study on Significant wave heights. *arXiv preprint arXiv* **2021**, 08583.
12. Mozo, A.; Morón-López, J.; Vakaruk, S.; Pompa-Pernía, Á.G.; González-Prieto, Á.; Aguilar, J.A.P.; Gómez-Canaval, S.; Ortiz, J.M. Chlorophyll soft-sensor based on machine learning models for algal bloom predictions. *Sci. Rep.* **2022**, *12(1)*, 13529.
13. Bhaganagar, K.; Kolar, P.; Faruqui, S.H.A.; Bhattacharjee, D.; Alaeddini, A.; Subbarao, K. A novel machine-learning framework with a moving platform for maritime drift calculations. *Front. Mar. Sci.* **2022**, *9*, 831501.
14. Chen, J.; Ashton, I.G.C.; Steele, E.C.C.; Pillai, A.C. A real-time spatiotemporal machine learning framework for the prediction of nearshore wave conditions. *Artif. Intell. Earth Syst.* **2023**, *2(1)*, 220033.
15. Kim, J.C.; Yu, D.H.; Sim, J.E.; Son, Y.T.; Bang, K.Y.; Shin, S. Validation of opendrift-based drifter trajectory prediction technique for maritime search and rescue. *J. Ocean. Eng. Technol.* **2023**, *37(4*), 145–157.
16. Trinh, N.Q.; Huan, N.M.; Hieu, P.D.; Toan, D.V. Simulation of drifting object motion in the east sea using numerical methods. Proceeding of the 14th Asian Congress of

Fluid Mechanics - 14ACFM, October 15-19, 2013, Hanoi and Halong, Vietnam, 2013, pp. 1144–1151.

17. Trinh, N.Q.; Cham, D.D.; Binh, H.T.; Thao, D.T.; Hanh, L.D.; Son, N.T.; Hung, L.T.; Giang, H.H.; Vinh, N.Q. Application of 2D models for the problem of plastic waste transmission to seasonal characteristics in the Da Nang–Quang Nam sea. *J. Hydro-Meteorol*. **2022**, *743*, 36–51.
18. Trong, N.G.; Quang, P.N.; Cuong, N.V.; Le, H.A.; Nguyen, H.L.; Tien Bui, D. Spatial prediction of fluvial flood in high-frequency tropical cyclone area using TensorFlow 1D-convolution neural networks and geospatial data. *Remote Sens.* **2023**, *15(22)*, 5429.
19. Tinh, L.D.; Thao, D.T.P.; Bui, D.T.; Trong, N.G. Integrating Harris Hawks optimization and TensorFlow deep learning for flash flood susceptibility mapping using geospatial data. *Earth Sci. Inf.* **2024**, *17*, 3397–3412.
20. Phong, D.V.; Trong, N.G.; Chien, N.V.; Thanh, N.H.; Ha, L.L.; Quan, N.V.; Quang, P.N. Analysis of land vertical movement using ANN function from the results of processing GNSS time series data. *J. Hydro-Meteorol*. **2023**, *752,* 41–50.
21. Tinh, L.D.; Thao, D.T.P.; Thang, T.D.; Hop, D.T.; Trong, N.G. Evaluating the Performance of CNN (Conv1D) and CNN (Conv3D) Models in GNSS Data Analysis. *J. Hydro-Meteorol*. **2024**, *771*, 55–64.
22. NOAA. Online available: https://www.ndbc.noaa.gov/.
23. ESA. Copernicus marine service. Online available: https://marine.copernicus.eu/.
24. Lawhead, J. Learning geospatial analysis with Python: Understand GIS fundamentals and perform remote sensing data analysis using Python 3.7. Packt Publishing Ltd, 2019.
25. Campesato, O. Python 3 for machine learning. Mercury learning and information, 2020.
26. Chen, D.Y. Pandas for everyone: Python data analysis. Addison-Wesley Professional, 2017.
27. Raschka, S.; Mirjalili, V. Python machine learning: Machine learning and deep learning with Python, scikit-learn, and TensorFlow 2. Packt publishing Ltd, 2019.