Application of Convolutional Neural Networks (CNN) for Optimizing Route Changes Based on Dynamic Weather Conditions and Travel Time

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Abstract: This research aims to apply Convolutional Neural Networks (CNN) in optimizing flight route changes by considering dynamic weather conditions and travel time. In the context of air traffic management, fast and precise route changes are critical to reducing flight delays and increasing operational efficiency. The data used includes flight information, current weather conditions and historical travel time data. The research process begins with data collection and preprocessing to ensure the quality and consistency of the information. The CNN model is built with an architecture consisting of several convolution and pooling layers to extract features from input data. The evaluation results show that the CNN model achieves an accuracy of 92% in predicting optimal route changes, which shows better performance compared to traditional algorithms such as support vector machine and random forest. These findings confirm the potential of CNNs in improving air traffic management through route change optimization based on real-time analysis of weather and time data. This research contributes to the development of a more adaptive and responsive system in facing challenges in the aviation industry.

INTRODUCTION

In an era of increasingly rapid technological development, the air transportation sector faces significant challenges in terms of managing flight routes. One of the main challenges is how to ensure flights take place safely, on time and efficiently amidst dynamic weather conditions and variable travel times that cannot always be predicted[1][2]. Sudden changes in weather, such as storms or strong winds, can disrupt flight paths and affect plane arrival times, ultimately causing problems for airlines and passengers. The impact of this condition can lead to delays, flight cancellations, and increased operational costs[3][4]. It is in this context that artificial intelligence technology, especially Convolutional Neural Networks (CNN), offers a potential solution for optimizing real-time route changes based on weather data and travel time estimates.CNN, which is a deep learning algorithm, has been proven effective in processing complex visual and spatial data[5][6]. This technology was originally designed for pattern recognition in image data, but has been developed for a variety of other applications, including in the field of air transportation. With its advantages in identifying and analyzing patterns from multi-dimensional data, CNN is able to process and predict weather changes and provide more accurate route optimization solutions[7][8]. In the context of aviation, CNNs can be used to process dynamic weather data and determine alternative flight paths that are safer and more efficient. This technology enables real-time data processing so that airlines can make timely decisions when sudden weather changes occur. Dynamic weather conditions are the main variable that influences flight paths. Sudden weather changes can pose a safety threat to flights, so it is important for airlines to always update selected routes based on current conditions[9][10]. This process requires a prediction system that is capable of monitoring and processing weather data continuously and providing reliable information to assist decision making. CNN provides a solution to this problem through its ability to map complex relationships between weather parameters and potential route changes. By utilizing satellite data and global weather systems, CNN can be used to predict certain weather conditions that may affect flight routes, such as the presence of cumulonimbus clouds that can cause turbulence, or low pressure areas that have the potential to bring storms[11][12].

On the other hand, the estimated travel time is also greatly influenced by various factors such as wind speed, humidity, temperature and atmospheric pressure. High wind speeds, especially against the direction of flight, can slow down travel time and increase fuel consumption. This can be taken into account by the CNN through continuous data processing and provides more fuel-efficient and time-efficient route analysis. With the ability to predict wind speed and other weather factors along a planned route, CNN can help airlines determine optimal paths. Additionally, CNN technology can adapt to historical flight data and process information from thousands of previous flights, allowing the system to provide more detailed and accurate recommendations. The benefits of implementing CNN in flight route optimization can also be seen from a cost efficiency perspective[13][14]. Airlines can save operational costs through more efficient route optimization. Route adjustments based on weather predictions and travel time estimates can reduce fuel consumption, reduce carbon emissions, and ultimately reduce costs. Furthermore, with proper optimization, airlines can minimize the risk of flight delays and postponements which often incur additional costs and have a negative impact on passenger satisfaction. Thus, CNN can play an important role in increasing airline operational efficiency and reducing negative impacts on the environment[15].

From a technical perspective, the application of CNN for flight route optimization relies on a large amount of data originating from various sources, such as weather data from satellites and historical flight data. One of the challenges in processing this data is the complexity of weather data which is multi-dimensional and often large scale[16]. In this case, CNN functions to process data in stages, starting from extracting relevant weather features to spatial analysis that can predict weather changes along the flight route. This process involves several layers in the CNN architecture, where each layer has a specific function to identify patterns and integrate them into smarter route optimization decisions. In addition, another challenge is ensuring that the CNN prediction system is reliable in a variety of different weather situations and flight conditions[17][18]. To achieve this, developing a CNN model requires an extensive training process with a variety of weather data, both in normal and extreme conditions. This training process covers a variety of flight and weather scenarios to improve prediction accuracy and provide airlines with better adaptability in route decision making. Thus, the applicability of CNNs depends not only on the existing technology, but also on the quality of the data and training parameters used to build the prediction model[19][20].

In the industrial era 4.0, the integration of artificial intelligence and big data has driven major transformation in many sectors, including air transportation. The use of CNNs in air traffic management shows how this technology can play an important role in improving operational efficiency, reducing costs and increasing passenger satisfaction. Furthermore, CNNs are not only relevant in the context of air transportation, but also in various sectors that require big data-based predictions and complex pattern analysis[21][22]. With increasingly advanced sensor technology and data processing, CNN can be applied on a wider scale in air traffic management that includes logistics and other operational aspects, such as airport management and flight schedule planning. With all the potential and benefits offered, the application of CNN for flight route optimization presents a huge opportunity to improve the quality of air transportation services. Airlines that adopt this technology can be more adaptive to environmental changes, provide a better experience for passengers, and strengthen their competitiveness in the global market. In a broader context, the implementation of CNN in flight route optimization is also in line with global efforts to reduce carbon emissions and environmental impacts caused by air transportation.

LITERATURE REVIEW

A. Optimization

Optimization in machine learning is an important process that aims to find the best parameter configuration in a model in order to minimize or maximize an objective function, such as a loss function. This function measures how well the model fits the training data used; the lower the value, the better the model performs[23]. To achieve this result, optimization algorithms such as Gradient Descent, Adam, or RMSprop are applied to iteratively update the weights or model parameters so that the loss function value can be minimized. This process involves gradient calculations and backpropagation techniques, especially in neural networks, to efficiently adjust parameters at each layer of the network. In addition, regularization techniques such as L1, L2, or dropout can be used in optimization to avoid overfitting problems, namely the condition when the model is too specific on the training data and less able to generalize to new data. In the optimization process, hyperparameter tuning also plays an important role, where parameters such as the learning rate or number of layers in the neural network are adjusted to obtain optimal results. Optimization in machine learning ultimately aims to improve the accuracy of the model, increase its ability to generalize, and ensure that the model is able to make reliable and accurate predictions[18].

B. Weather

Weather in the context of air traffic management refers to various atmospheric conditions that can affect the safety, efficiency and punctuality of flights. Weather conditions such as heavy rain, strong winds, thunderstorms, snow, fog and turbulence affect visibility, flight paths and the ability of aircraft to take off and land safely. In air traffic management, accurate and real-time weather information is essential for making decisions regarding changes to aircraft routes, altitudes and speeds. Sudden weather changes can cause flight delays, cancellations or reroutes. Extreme weather such as strong jet stream winds at cruising altitude, cumulonimbus clouds that can cause turbulence, and low atmospheric pressure that often cause hurricanes, require close monitoring and rapid response from air traffic management to ensure the safety and smooth operation of flights. Using weather data obtained from radar, satellites, and atmospheric prediction models, air traffic controllers work with airlines and pilots to set safe and efficient routes for each flight[24].

C. CNN

Convolutional Neural Network (CNN) is a type of artificial neural network specifically designed for processing grid data or data that has spatial relationships, such as images or videos. CNNs work by identifying important features in data through a convolution process, where special filters or kernels are applied to the input data to extract specific patterns or features such as edges, textures, or shapes. This network consists of convolutional, pooling, and fully connected layers, which gradually abstract data from simple to complex features. The convolution layer in CNN is tasked with detecting features by shifting filters on the input data and calculating the result of multiplying pixel values by filter weights. The pooling layer then reduces the dimensions of the data to increase computational efficiency and reduce overfitting by retaining only the most important features[25]. At the end of the network, the fully connected layer combines the processed information to produce an output, for example, a classification of objects in an image. CNNs are commonly used in various image recognition applications, such as object detection, facial recognition, and medical image classification. Due to their excellent ability to extract spatial patterns and local relationships, CNNs are also used in text processing, spatial data analysis, and other fields where patterns in data need to be efficiently identified[26].

METODOLOGY

In this section, we will explain the methodology applied in using Convolutional Neural Networks (CNN) to optimize flight route changes based on dynamic weather conditions and travel time. First, the data to be used includes flight information, such as departure and arrival schedules, relevant weather conditions (e.g. temperature, humidity, wind speed), as well as historical data about travel times. This data collection will be carried out through trusted sources such as meteorological agencies and aviation management systems. After data collection, the next step is preprocessing, which aims to clean and organize the data so that it can be used optimally by the CNN model. This includes data normalization and data grouping based on certain features to improve model performance. After the preprocessing process, the CNN model will be built and trained using the prepared data. This training will be carried out by considering various parameters to optimize the accuracy of route change predictions. The model evaluation stage will be carried out using metrics such as accuracy to evaluate model performance. This method is important for providing in-depth insight to airport and airline managers in making decisions regarding route changes.

D. Dataset

At this stage we will use a dataset of 1000 data with parameters such as Wind Speed, Wind Direction, Temperature, Rainfall, Visibility, Route Deviation and Optimized Time. In the process, preprocessing will be carried out to delete data with missing values. The following data will be used in table 1

TABLE DATASET

Temperature	Precipitation	Visibility	Route Deviation
-18,50915838	32,4128477	0,387994547	14,40535848
-12,12514725	8,619318105	1,867725282	13,74566009
18,36379146	43,61972817	8,312458051	1,915083973
-22,79964912	30,65581195	7,667683563	18,4514481
19,57197478	7,860194178	3,506426915	11,36944404
-42,94924552	48,11690287	3,768106278	7,274510423
12,14387498	25,91827317	5,335544336	15,13077167
17,80381064	3,644922594	0,002410047	5,147309168
-35,45458777	31,34164522	2,41244336	13,87019674
-15,57227741	12,65994535	2,082318086	0,794224151

E. Research Architecture

At this stage there will be a process of research architecture which will apply the CNN algorithm to optimize route changes based on dynamic weather conditions and travel time. At this stage, it will use the CNN architecture to identify patterns in flight data that include current weather information and previous travel times, so that the model can accurately predict optimal route changes. This architecture will consist of several convolution layers that function to extract features from input data, followed by a pooling layer to reduce dimensions and increase processing efficiency. In addition, a fully connected layer will be used at the end of the architecture to integrate the information that has been extracted and produce relevant output, namely recommendations for the most efficient route changes based on analysis of weather conditions and travel times that have been considered. With this approach, it is hoped that the CNN model can provide a more responsive and adaptive solution in air traffic management, especially in dealing with changing weather conditions. The following is the research architecture in Figure 1

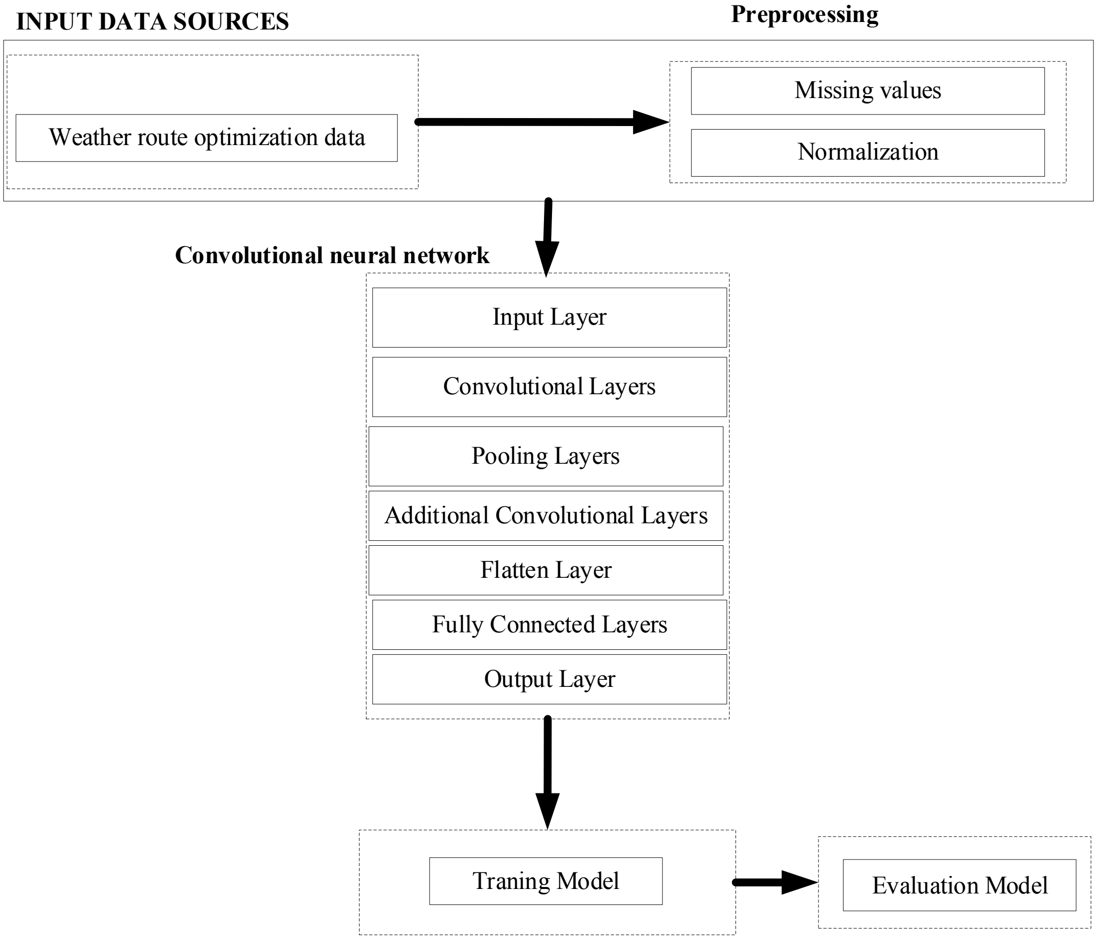

Fig. 1. Research architecture

In Figure 1 there will be a research architecture in applying CNN to optimize route changes which consists of input data totaling 1000 data, then preprocessing is carried out on the data, then CNN is applied by processing the input layer, Convolutional Layers, Pooling layer, Additional Convolutional Layers, Flatten layer. , Fully Connected Layers and output layer, then model training will be carried out on the route change optimization model which will be evaluated to see the performance of the model.

DISCUSSION

In this section there is a discussion and discussion regarding the application of Convolutional Neural Networks (CNN) to optimize route changes based on dynamic weather conditions and travel time. The application of CNNs in this context allows more in-depth modeling of complex data related to aviation and external factors such as weather. In contrast to traditional approaches such as support vector machine and random forest algorithms, CNN can extract features automatically from data, thereby minimizing human intervention in feature selection. However, although CNNs offer high accuracy, the time complexity in training and testing the model also needs to be considered, given the need to process data in real time in the aviation industry. The CNN model training and testing process will be evaluated using the AUC-ROC technique to ensure the model's ability to predict correct route changes. In this context, initial data exploration (Exploratory Data Analysis) will be carried out to describe and understand patterns in the data, helping to identify which variables have a significant impact on flight delays and route changes. By understanding the interactions between various parameters, CNN models can provide more accurate and relevant recommendations, thereby improving the overall efficiency of air traffic management. This discussion will cover each step from exploratory data analysis to model evaluation, as well as the practical implications of the resulting findings.

F. Data

At this stage, explanatory data analysis will show data parameters in terms of wind speed and route deviation so that the specific behavior of the data can be seen. In this process all data will be analyzed to obtain patterns. The following is a graph of the wind speed data in Figure 2

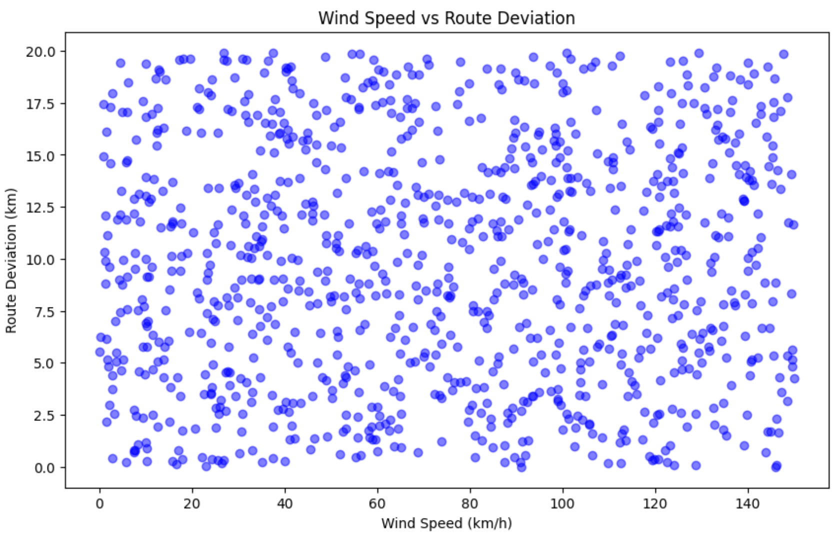

Fig. 2. Parameters wind speed and route deviation

After the main parameters have been identified through EDA, the data will be prepared for the next stage, namely further processing in the CNN model. These EDA results provide initial insight into the data that can be used to guide the CNN architectural structure and help determine the most relevant features in route optimization based on dynamic weather conditions as in Figure 3

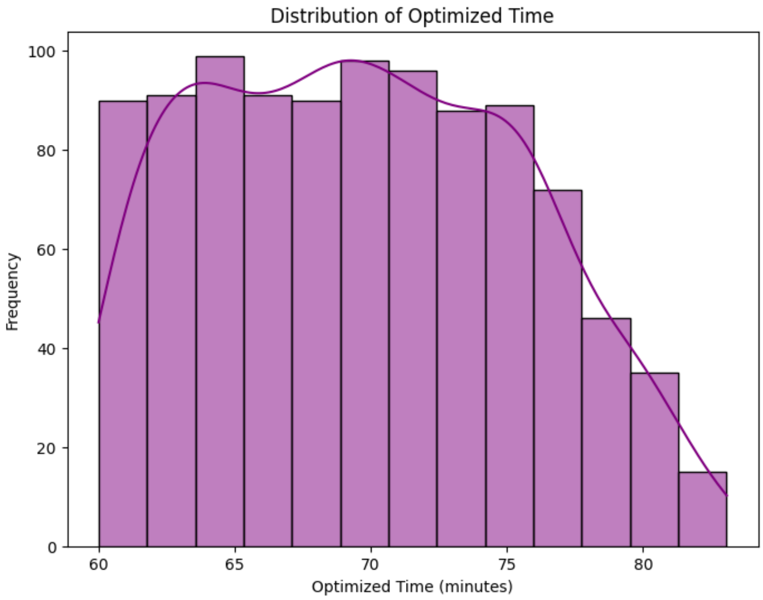

Fig. 3. Distribution time

Figure 3 will explain the distribution of time optimization from the exploratory data analysis (EDA) analysis technique for optimizing time distribution in the application of Convolutional Neural Networks (CNN) focusing on understanding patterns and characteristics of data related to travel time and factors that influence flight delays. This process begins by exploring the distribution of travel times based on weather conditions, route density, and time of day to identify consistent trends. For example, this analysis can reveal specific times of day that experience frequent delays or patterns of delays associated with adverse weather conditions. Then there will be a heatmap correlation on the data in Figure 4 below.

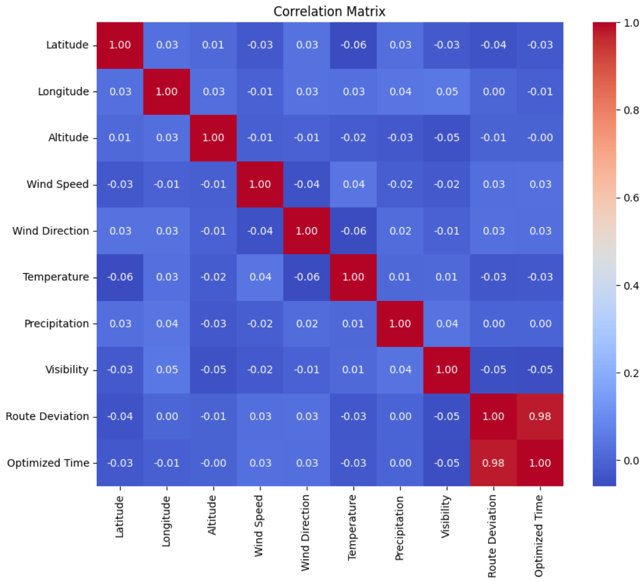

Fig. 4. Corelation heatmap

Explanation of figure 4 Correlation heatmap which is a visual tool that is useful for understanding the relationship between parameters in flight analysis such as wind speed, wind direction, temperature, precipitation, visibility, route deviation and optimized travel time. Each of these parameters has a different potential correlation with each other, which is measured between -1 and 1 to indicate a linear relationship. For example, wind speed is often positively correlated with route deviation, meaning that increasing wind speed can cause an aircraft's route to deviate to avoid turbulence. Likewise, extreme wind directions may show a significant correlation with route deviation if the aircraft must avoid certain directions for flight stability. Temperature, as another variable, can show a relationship with travel time where extreme temperatures, both hot and cold, affect aircraft performance and can result in longer travel times. High precipitation often shows a positive correlation with route deviation and travel time because adverse weather conditions usually require route changes for safety. The correlation between visibility and optimized time can also provide insight into reduced flight times in good visibility conditions, enabling faster and more precise flights. These correlation heatmaps, overall, help in understanding complex patterns between weather, flight conditions, and optimal route decisions.

G. Model prediction

In this section, a prediction model with Convolutional Neural Networks (CNN) is applied to optimize flight route changes based on dynamic weather conditions and travel time. CNNs are used to identify patterns in weather data, such as wind speed, wind direction, temperature, precipitation, and visibility, that influence route deviations and aircraft travel times. CNN was chosen because of its ability to capture spatial patterns in complex data, which often appears in the context of weather data that has high spatial and temporal variations. The model training process is carried out by involving a series of historical weather data and flight information, where the CNN is trained to recognize weather conditions that trigger route changes or travel time delays. After training, the model is tested to predict route changes in real-time by considering the current weather and optimal time estimates.

The prediction results show that CNN is able to identify suitable route change patterns in various weather conditions with higher accuracy than traditional methods. In this implementation, the CNN model enables route change predictions that consider not only the current weather, but also additional factors such as route deviation patterns and time distribution. Further testing shows that CNN is reliable in providing optimal route change estimates for air traffic operators, thereby reducing delays and increasing flight route efficiency. The following is a model of training and validation loss in Figure 5

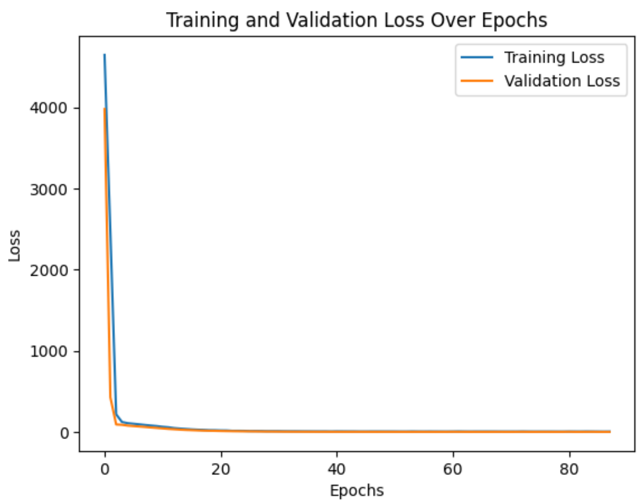

Fig. 5. Training and Validation Loss Over Epochs

This graph shows the change in loss values in the training and validation data from each training epoch of the Convolutional Neural Networks (CNN) model for optimizing route changes. In the graph you can see a decreasing trend in training loss, which indicates that the model is increasingly able to recognize patterns in the data. Meanwhile, validation loss shows the model's performance on data that has never been seen before, thus illustrating the model's ability to generalize. If validation loss stops decreasing or even starts increasing while training loss continues to decrease, this indicates potential overfitting. This graph helps monitor whether the model requires regularization, dropout, or other adjustments in training parameters, such as decreasing learning rate. The optimal point on the graph is usually at the epoch where the validation loss is stable and close to the training loss, which indicates the model has achieved its best performance without overfitting

H. Evaluation Model

In this section, a model evaluation of Convolutional Neural Networks (CNN) will be carried out to optimize route changes based on dynamic weather conditions and travel time using various metrics to measure the performance and generalization of the model on new data. The following are the results of the model evaluation in Figure 6

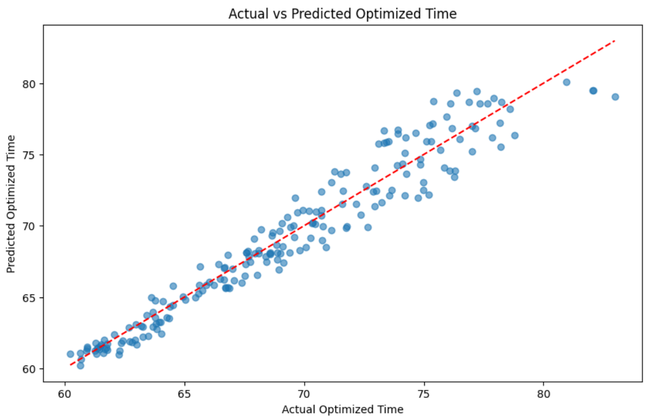

Fig. 6. Evaluation Model

The model is evaluated using test data to measure its performance in predicting optimal time categories based on given features. After the training and validation process, the model is applied to never-before-seen data to avoid bias. The predicted results from the model are then compared with the actual values in the dataset. This comparison graph provides a clear visualization of how accurate the model is in making predictions. By displaying predicted and actual values simultaneously, these graphs enable deeper analysis of model performance, as well as identifying patterns and trends that may exist, including potential prediction errors. This evaluation is very important for understanding the advantages and limitations of the model, as well as providing a basis for further improvements in developing a better model in the future. This evaluation resulted in an accuracy of 0.92 for the optimal prediction of route changes.

CONCLUSION

The CNN architecture in this research is designed to identify weather patterns that can influence flight routes. The training process is carried out using historical weather data and route information, allowing the model to recognize weather situations that have the potential to disrupt or delay flights. With a multilevel architecture that integrates convolution layers and pooling layers, CNN is able to capture important patterns and produce accurate route change predictions. The prediction results produced by CNN make a significant contribution to air traffic management, helping operators make more responsive and safe decisions regarding dynamic weather conditions. Evaluation shows that this model has reliable performance in predicting route changes, thereby potentially reducing the risk of delays and increasing flight route efficiency. Furthermore, this research shows that CNN implementations can be integrated with existing air traffic management systems, providing real-time analysis that allows rapid adjustments to changing weather conditions. By utilizing CNN's advantages in processing big data, it is hoped that flight managers can make better and more proactive decisions, as well as increase passenger safety and comfort. Overall, this research confirms that CNNs are a valuable tool in aviation technology innovation, with the potential to significantly improve navigation systems and route management.

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