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Research on Dynamic Modeling and Simulation of Aircraft Landing Gear Retraction and Retraction Mechanical System

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SUMMARY: *The health of aircraft landing gear is related to flight safety. In order to real-time grasp the fatigue accumulation of landing gear and achieve maintenance according to the situation, it is necessary to accurately predict the landing load data of landing gear in real time. This study is based on actual test flight data of a certain aircraft model, and introduces the Yolo v11 algorithm model. CBAM attention mechanism, C3Chost module, and DyHead object detection head are used to improve it, forming a landing gear landing load prediction model based on the improved Yolo v11 algorithm. In terms of data processing, 220956 samples (209956 training sets and 11000 test sets) were cleaned and feature dimensionality reduced, and 13 flight parameters were selected as features using various methods. In the experiment, the improved model will be compared with the Yolo v11 and Yolo v11En models, and evaluated using metrics such as R^2, MSE, and average relative error. The experimental results show that, based on the R^2 metric, the three models perform similarly on the training and testing sets, without overfitting. In terms of MSE indicators, the Proposed Method model performed outstandingly in the test set, with MSEs of 0.3700 (Task 1 test set composite value) and 0.3607 (Task 2 test set composite value), respectively. Compared with the other two models, the MSE on the vertical load test sets of the left and right main landing gear decreased by more than 66%; The MSE difference between the training set and the test set is smaller, indicating stronger stability. In terms of average relative error, the proposed method model has an average prediction error of 1.21% and 1.19% for the vertical load on the left and right main landing gear, respectively, which is significantly better than the other two models. Research has shown that the landing gear load prediction model based on the Proposed method model has high prediction accuracy, strong stability, and good reliability, and has higher value and potential in practical applications.*

KEYWORDS: *aircraft landing gear; Landing payload; Yolo v11 algorithm; Attention mechanism; Dynamic simulation; Feature dimensionality reduction*

1 Introduction

The operational status of landing gear is closely related to flight safety, however, the attenuation of fatigue life of landing gear is often difficult to detect through conventional detection methods. In view of this, many aircraft components have adopted a "damage tolerance" strategy in their design, which assumes the presence of cracks in the structure and only implements corresponding repair measures after detecting the cracks [1, 2]. However, as a key component of the single transmission structure, the landing gear still follows the traditional "safe life" design principle, which means that the component is set with a clear service life. Once it exceeds

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the predetermined fatigue life, it needs to be stopped from use and repaired. However, given the varying actual conditions of each flight, relying solely on "safe life" design may lead to resource waste caused by "excessive maintenance" or safety hazards caused by "insufficient maintenance". Therefore, developing a model that can predict the landing load of landing gear in real time to accurately grasp its fatigue accumulation status is of great value for achieving on-demand maintenance of landing gear.

At present, CAE simulation models are mostly based on physical laws for mathematical modeling, and their simulation effects highly depend on the accuracy of the model's simulation of the actual object. However, there are many problems in real systems that are difficult to accurately describe through mathematical models, making the construction of CAE models for landing gear both challenging and computationally intensive. With the advancement of artificial intelligence technology, new avenues have been opened up for the development of landing gear maintenance strategies [3, 4]. Machine learning, as a computer simulation technology, relies on learning from a large amount of data to autonomously discover patterns, simulate the real behavior and characteristics of the system, and then construct complex mapping relationships between inputs and outputs. By using machine learning to construct proxy models, automatic parameter adjustment can be achieved, which not only reduces design complexity, but also continuously learns based on new data and dynamically updates parameters to adapt to new environments. At present, machine learning technology has been widely applied in various fields such as energy, machinery, chemical industry, power, logistics, etc [5]. In recent years, scholars at home and abroad have been exploring the application of machine learning technology in the field of load prediction. For example, some studies have successfully predicted the loads on key parts of wind turbines under different wind conditions by combining BP neural networks with multi factor weight analysis; Another study is based on engineering measurement data, using mutual information method for feature ranking, and using support vector regression to construct a prediction model for shield tunneling load [6]. At the same time, some scholars have also begun to study the application of machine learning technology to predict aircraft component loads, such as calculating the load on the aircraft during landing and wing loads. These studies indicate that compared to traditional mechanistic model simulations, machine learning techniques can ensure high accuracy in load prediction while saving a lot of computational resources and time, and can effectively model physical environments where mechanistic models are difficult to establish. However, existing research is mostly limited to modeling simulation data, which is generated by mechanistic models without noise interference, and does not fully consider the influence of other random factors. In practical engineering, measured data is more complex and variable, and the processing difficulty is greater. Therefore, it is necessary to develop model construction techniques with higher prediction accuracy, faster prediction speed, and stronger generalization ability [7].

Based on this, this study relies on actual test flight data of a certain aircraft model to address the difficulties in modeling the real landing gear system and accurately reflecting its load changes in simulation data. The Yolo v11 algorithm model is introduced to carry out processing, modeling optimization, and comparative analysis of landing gear load data. At the same time, in order to improve the prediction accuracy and efficiency of the model, this study used CBAM attention mechanism, C3Chost module, and DyHead object detection head to improve the original Yolo v11 algorithm. Finally, a landing gear load prediction model based on the improved Yolo v11 algorithm was constructed, providing new ideas for the development of landing gear maintenance strategies.

2 Related research

At present, the monitoring of the landing gear status of aircraft before landing mainly relies on the self-inspection system equipped on the aircraft itself. However, in the academic research field, there is still relatively little literature on the use of deep learning techniques to monitor the status of aircraft landing gear [8]. The concept of deep learning was first proposed by Hinton and other scholars in 2006. It has built a complex network architecture that includes multiple perceptrons and hidden layers, enabling a more in-depth and abstract representation of the basic features and attributes of the target.

Among the many application directions of deep learning, the development of computer vision is the most mature and widely used. In 2012, the deep learning model Alexnet shone in the ILSVRC image classification competition, winning the championship with an absolute lead of over 10 percentage points over the second place [9]. This landmark event has brought deep learning into the academic field and received widespread attention.

At present, object detection algorithms based on convolutional neural networks can be roughly divided into two categories. One type is two-stage algorithms, represented by the R-CNN series. Subsequently, high-performance algorithms such as Fast R-CNN and Faster R-CNN were developed based on this foundation [10]. Although these algorithms have high detection accuracy, their processing speed is relatively slow. The other type is single-stage algorithms, such as YOLO series, SSD, etc., which are known for their fast detection speed, but may be slightly inferior in accuracy. In application scenarios such as autonomous driving that require high real-time performance, single-stage object detection algorithms are often the preferred choice. Among them, the R-CNN network proposed in 2014 has epoch-making significance in the field of computer vision. However, R-CNN also has obvious shortcomings, such as generating a large number of duplicate regions when generating candidate regions, which leads to unnecessary time waste in the feature extraction process [11]. To address this issue, Fast R-CNN introduces the ROI pooling layer (Region of Interest pooling layer). This pooling layer is capable of dividing the convolutional layer features corresponding to candidate regions into a fixed number of blocks and directly performing max pooling operations on each block. This improvement not only eliminates the step of normalizing candidate regions, but also enables the convolutional network to complete region regression tasks while outputting target category probabilities, significantly improving detection speed and accuracy.

In 2016, Redmon and other researchers introduced the YOLO algorithm. This algorithm utilizes neural networks to directly predict the position, size, and probability of detection box categories in an end-to-end manner, greatly accelerating detection speed [12, 13]. Subsequently, YOLO-V2 further improved the localization accuracy and target recall rate of the algorithm by introducing normalization processing, optimizing the training process, adopting anchor box mechanism, and using k-means clustering algorithm to generate adaptive anchor boxes. YOLO-V3 utilizes techniques such as residual skip connections and upsampling to improve the detection performance of the model by detecting at three different scales. The YOLO-V4 algorithm can be regarded as the culmination of the YOLO series [14]. On the basis of the original YOLO object detection framework, it integrates the most cutting-edge optimization strategies in the CNN field in recent years and adopts various data augmentation techniques. We have comprehensively upgraded from multiple aspects such as data processing, backbone network design, network training methods, activation function selection, and loss function optimization, ultimately achieving the optimal balance between detection accuracy and detection speed.

3 Data Processing and Modeling Methods

3.1 Operating principle of landing gear

The core structure of this innovatively designed aircraft landing gear consists of four "leg like" parts, each of which adopts the design principle of a planar six bar mechanism [15, 16]. In practical operation, the system uses Raspberry Pi output pulse signals to accurately regulate the operation of the motor. The power generated by the motor rotation is transmitted through the transmission mechanism between each rod, so as to flexibly adjust the specific position of each leg of the landing gear and achieve precise control of the landing process of the landing gear.

When the drone determines the specific landing location and sends a landing command signal to the outside, the Raspberry Pi will quickly receive the signal and immediately send the corresponding command to drive the motor to start running [17, 18]. The rotation of the motor will drive the screw to perform linear reciprocating motion, and with the help of the transmission effect between the various rods in the six-bar mechanism, it will cause the rods of the landing gear legs to move in both horizontal and vertical directions. In this way, it is possible to flexibly adjust the posture of each leg of the aircraft landing gear, thereby completing the pre adjustment of the aircraft's posture before landing. The specific model of a single leg aircraft landing gear can refer to **Figure 1**.

Figure 1: Single leg model of aircraft landing gear

From the **Figure 1**, as the aircraft gradually enters the blind zone of the terrain observation device, the control of the motor operation will be transferred to the foot pad switches at the bottom of each leg, which will operate the motor. When all legs of the landing gear land smoothly, the brakes will immediately activate to firmly stop the screw, ensuring that the entire mechanism maintains a stable posture and ultimately achieving a smooth and safe landing of the aircraft.

3.2 Load prediction performance evaluation

The dataset used in this study consists of two parts: one is the flight parameter data collected by the flight parameter recorder, and the other is the load information measured by the landing gear sensors. These data were obtained through multiple flight tests conducted on a specific model of aircraft, and the entire dataset contains a total of 220956 sample data. During the data processing, 209956 samples were selected as the training set to support the model's training and learning; Additionally, 11000 samples were selected as the test set for performance evaluation of the trained model [19].

In this dataset, up to 52 flight parameters are covered, including key parameters such as speed, altitude, angle of attack, and sideslip angle [20]. The labeled data is selected as the vertical load borne by the left landing gear. The target model constructed in this study focuses on solving regression problems in the field of machine learning. Unlike classification problems, the model evaluation process for regression problems is more complex and requires comprehensive consideration of multiple factors. In order to comprehensively and accurately evaluate the performance of the model, this study uses three indicators for comprehensive evaluation, namely mean absolute percentage error (MAPE), mean squared error (MSE), and coefficient of determination (R2). Next, we will elaborate on the specific calculation methods of the three indicators MAPE, MSE, and R2.

$$MAPE = \frac{1}{n} \times 100\% \sum_{i=1}^{n} \left| \frac{y_i - y_i}{y_i} \right| \tag{1}$$

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

$$R^2 = 1 - \sum_{i=1}^{n} \left(\hat{y}_i - y_i \right)^2 \Big/ \sum_{i=1}^{n} \left(y_i - \bar{y}_i \right)^2 \tag{3}$$

where, $\hat{y}_i$ represents the load value predicted by the model; y_i represents the actual load value obtained through measurement; $\bar{y}_i$ represents the mean obtained by calculating all real loads; *n* represents the number of samples used for testing.

In terms of model evaluation indicators, the numerical values of MAPE (Mean Absolute Percentage Error) and MSE (Mean Square Error) are negatively correlated with the model's prediction performance, meaning that the smaller the values of these two indicators, the more accurate the model's prediction results. Specifically, the advantage of MAPE lies in its ability to directly present the percentage of model prediction error in the true value [21, 22]. However, when the true value is equal to 0, this indicator may encounter the problem of ineffective calculation, resulting in its inability to function properly. Unlike this, MSE can clearly reflect the size of the model's prediction error value, and even if the true value is 0, it can still perform calculations normally. In addition, R2 (coefficient of determination) mainly reflects the percentage of interpretable information in the overall information of the model's prediction results. The closer the value of R ^{2} approaches 1, the better the predictive ability of the model.

3.3 Data cleaning and feature dimensionality reduction

Identify the 52 flight parameters involved in sequence using A-Z and AA-AZ, and mark the vertical load borne by the left landing gear as Load. Considering the characteristics of noise and large fluctuation amplitude in the actual measured load information of sensors, this study selected Savitzky Golay filter (S-G filter for short) to filter the data.

S-G filter is a filtering method in the time domain, which is based on local polynomial least squares fitting. The most prominent advantage of this filter is that it can ensure that the shape and width of the signal remain unchanged while effectively filtering out noise. Essentially, the S-G filtering operation removes high-frequency information from the data while retaining lowfrequency information, which perfectly meets the requirements for filtering sensor measured data [23].

In order to explore the intrinsic relationship between different flight parameters and load variation patterns, this study used mutual information method to preliminarily screen the features. Mutual information, as a measure of information in information theory, describes the degree of uncertainty that a random variable reduces due to the knowledge of another random variable. For two random variables X and Y, their mutual information can be expressed in the following form [24]:

$$I(X;Y)=\sum_{x\in X}\sum_{y\in Y}P(x,y)\lg\frac{P(x,y)}{P(x)P(y)} \tag{4}$$

where, $P(x)$ represents the marginal distribution probability of random variable *X*, and $P(y)$ represents the marginal distribution probability of random variable *Y*; $P(x,y)$ represents the joint distribution probability of the independent variable *X* and the dependent variable Y; $I(X;Y)$ is used to represent the mutual information between variable *X* and variable *Y*.

When two variables are independent of each other, their mutual information value is equal to 0; On the contrary, the larger the mutual information value, the stronger the correlation between these two variables [25]. In this study, the mutual information calculation tool provided by the scikit learn machine learning library in Python language was used to calculate the mutual information values between the vertical load of the left landing gear and 52 flight parameters. Using 0.1 as the threshold standard for mutual information, the flight parameters K, P, Q, R, S, T, U, AK, AL, AM, AN, AO, and AP with weak correlation with the labels were screened and removed. After this step, 39 flight parameters remained.

In feature selection, features with low variance have lower sensitivity to sample discrimination. From a theoretical perspective, the contribution of such features in the modeling process is relatively small. However, if only the variance size is used to filter features without considering the possible impact of parameter units, it is highly likely to miss some important features, such as flight parameter E. Therefore, based on the calculation results of comprehensive mutual information, this study sets the variance threshold to 1.2 and the mutual information threshold to 0.3. On this basis, flight parameters I, M, and AT are further screened out, and the remaining 36 flight parameters are used for subsequent research [26].

4 Improved Yolo v11 Landing Gear Load Prediction Model

4.1 Original Yolo v11 Model

YOLOv11, as a new generation object detection algorithm carefully developed by Ultralytics, has achieved significant breakthroughs and innovations in architecture design and training methods on the basis of inheriting and developing the advantages of previous YOLO series versions. The network structure of this model is shown in **Figure 2**.

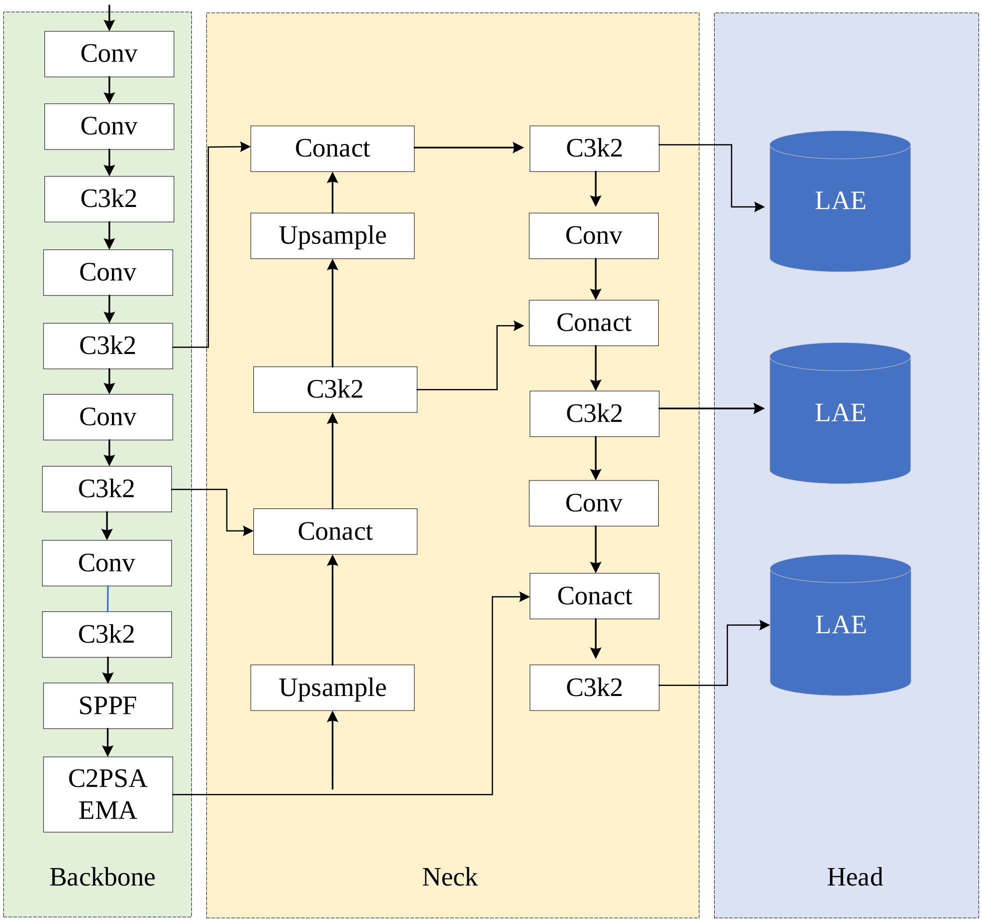


Figure 2: YOLO v11 Model Structure

As shown in **Figure 2**, this algorithm cleverly integrates optimized and improved model structure design concepts, more powerful feature extraction techniques, and carefully optimized training strategies. What truly sets YOLOv11 apart among numerous algorithms is its successful combination of exceptional speed, high accuracy, and outstanding efficiency, making it one of the most powerful algorithm models created by Ultralytics to date [27, 28]. Thanks to its ingenious design improvements, YOLOv11 has superior feature extraction capabilities. This process aims to accurately identify key patterns and details from images, and even in challenging and complex scenes, it can capture the intricate and complex feature elements more precisely.

The performance of YOLOv11m on the COCO dataset is particularly impressive, as it successfully achieved higher mean accuracy (mAP) scores. At the same time, compared with YOLOv8m, it reduces the number of parameters used by 22%, achieving a significant reduction in computational complexity and becoming more lightweight without compromising performance. This feature means that it not only provides more accurate detection results, but also greatly improves operational efficiency. It is particularly worth mentioning that YOLOv11 also brings faster processing speed, with inference time reduced by about 2% compared to YOLOv10, making it an excellent choice in the field of real-time applications.

The YOLOv11 model mainly consists of three parts: the backbone layer, neck layer, and head layer. Among them, the Backbone layer adopts the C3k2 module and utilizes Bottleneck Block to quickly perform Spatial Pyramid Pooling Fast (SPPF) and Cross stage Partial with Pyramid Squeeze Attention (C2PSA) modules, effectively improving the feature extraction capability. The Neck layer focuses on fusing and enhancing features, while the Head layer is responsible for generating the final detection results.

4.2 CBAM Attention Mechanism

In response to the frequent occurrence of false positives, missed detections, and poor detection accuracy in the process of measuring aircraft landing gear loads, this paper innovatively introduces a lightweight attention mechanism - CBAM module - in the backbone network architecture. Its specific structure can be seen in **Figure 3**.

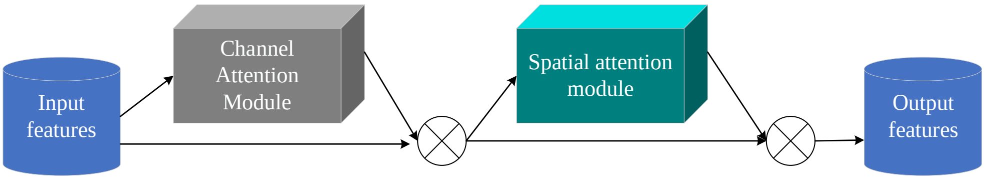


Figure 3: CBAM attention mechanism

As shown in **Figure 3**, the CBAM module cleverly integrates channel attention mechanism and spatial attention mechanism, which can dynamically adjust the channel weight and spatial weight of feature data according to the actual situation. Through this adjustment method, the improved YOLO v11 model is able to focus more attention on key features while effectively suppressing irrelevant information interference. Practice has shown that the addition of the CBAM module has brought significant performance improvements to the YOLO v11 model. It greatly enhances the expression and generalization ability of the model, enabling it to focus more accurately on extracting feature information of individual landing gear loads and load measurement points. This improvement measure has laid a solid foundation for further improving the detection accuracy of the model and effectively promoted the development of aircraft landing gear load detection technology.

4.3 C3Chost module

In the YOLO v11 pose model, the Neck layer uses the C3 module, which has certain performance in extracting image features [29]. However, while introducing a large number of model parameters, the C3 module inevitably brings a significant increase in computational complexity. In view of this situation, in order to effectively reduce the computational and parameter complexity of the model, accelerate the extraction speed of key points for aircraft landing gear load measurement, and promote the deployment and application of the detection model in practical scenarios, this paper optimizes the Neck part of the original YOLO v11 pose model, integrates the ChostNet E0-31 network into the C3 module, and constructs the C3Ghost module. This module can efficiently obtain more feature maps with fewer parameters and computational complexity. On the premise of ensuring that the model accuracy remains basically unchanged, this module can significantly reduce the number of model parameters and decrease memory usage. The structure of the C3Ghost module can be seen in **Figure 4**.

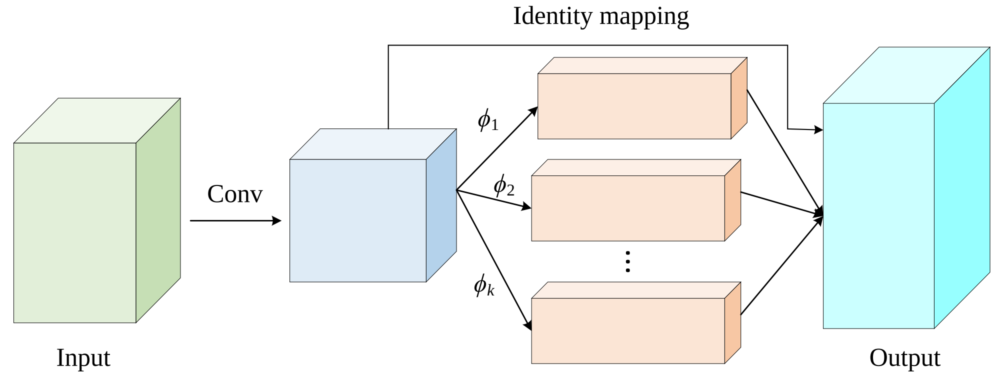


Figure 4: C3Chost module

As shown in **Figure 4**, GhostNet, as a lightweight neural network, has a lightweight implementation process as shown in Figure 7. Specifically, first use a small number of convolution kernels to output feature data, then perform low-cost linear operations on the generated feature data to generate more feature data, and finally concatenate these two sets of feature data to output. In this way, it can effectively reduce the number of parameters and storage requirements of the model, while having minimal impact on the accuracy of model detection.

4.4 DyHead Object Detection Head

Given that this experiment focuses on a prolonged period of continuous monitoring during the prediction of aircraft landing gear loads, during which the magnitude of the load borne by the aircraft landing gear fluctuates significantly [30]. This significant load variation is highly likely to have adverse effects on the accuracy of key load measurement points, leading to a decrease in their precision. Based on this, in order to further improve the performance of the YOLO v11 model, this article has carried out more in-depth improvement work. Specifically, the DyHead Bal object detection head was introduced into the Head layer of the model, and its detailed structure can be seen in **Figure 5** (it should be noted that the numbers in the upper right corner of α and β in the figure represent the i-th attention branch).

As shown in **Figure 5**, this object detection head innovatively integrates the three attention mechanisms of scale perception, spatial perception, and task perception, effectively enhancing the expressive ability of object detection. In practical operation, DyHead can accurately obtain spatial scale information of landing gear loads by fusing feature data of different scales. Meanwhile, with the help of deformable convolution technology, the coordinate information of load measurement key points in feature data can be efficiently extracted. Moreover, comprehensive perception of feature data keypoint detection tasks is achieved through a fully connected network. After introducing the DyHead object detection head, the improved YOLO v11 pose model has significantly improved its ability to express the position characteristics of key points of aircraft landing gear loads, thereby obtaining more accurate coordinate information of key points, providing reliable data support for subsequent research and analysis.

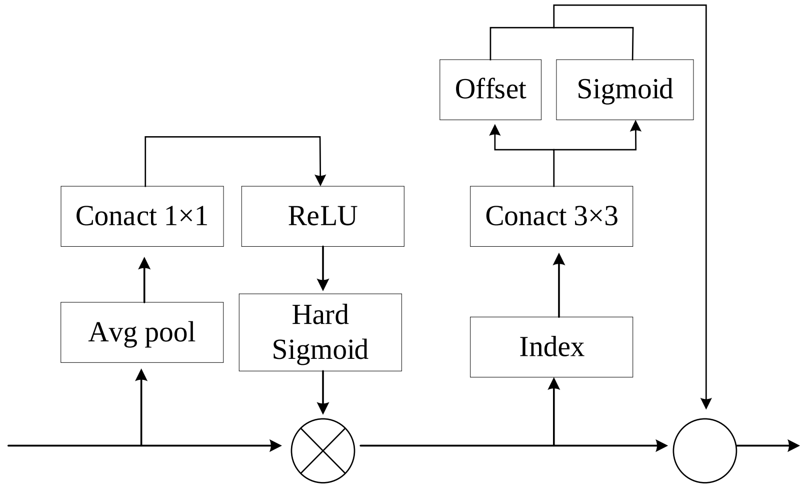


Figure 5: DyHead Structure Diagram

5 Experimental analyses

Firstly, according to the 9:1 ratio rule, the dataset is divided into two parts: the training set and the testing set. Among them, the training set contains 40523 samples, which will be input into the training process of the network model; The test set has 4406 samples, which is used to evaluate the model's generalization ability on unknown data. Due to the limited length of the article, only the relevant content of multicollinearity analysis is presented in the model calibration section.

When conducting modeling work, in order to ensure a fair and effective comparison of the performance of the three models, we deliberately control the model structure to have a similar number of trainable parameters.

For the Yolo v11 model, it has 8 hidden layers, and the number of neurons corresponding to each hidden layer is (16, 32, 64, 309, 309, 64, 32, 16). The total number of parameters in the model is 143459. In the evaluation phase, a multi input single output approach is adopted to evaluate Task 1 and Task 2 separately.

For the Yolo v11En model, it consists of one underlying shared network and two tower networks, with a total parameter count of 143216.

For the Proposed method model, its structure is relatively complex, including 8 expert networks, 2 tower networks, and 2 gate networks. Among them, the activation function selected for the gate control network is softmax, and the total number of parameters in this model is 143925.

In the above three models, the activation function used for the hidden layer is ELU. When evaluating the performance of the model, R^2 and MSE are selected as evaluation indicators, and the Adam optimizer is used to optimize the model. In the optimization process, set the initial learning rate to 0.001 and the initial number of training cycles to 2000. The experimental results of the three models are detailed in **Table 1**.

According to the experimental comparison data in **Table 1**, based on the R^2 index, the performance of the three models on the training and testing sets is extremely close. Taking Task1 as an example, the R^2 of Yolo v11 on the training and testing sets are 0.9848 and 0.9837, respectively; Yolo v11En are 0.9850 and 0.9842, respectively; The proposed methods are 0.9880 and 0.9873, respectively. Similar trends were also observed in Task 2, which fully indicates that none of the three models had overfitting issues and were able to fit the data well, demonstrating a certain degree of consistency in grasping the overall trend.

Table 1: Experimental results of the dataset on different models

Network model	Evaluation indicators	Task1		Task2	
		Training set	Test set	Training set	Test set
Yolo v11	R2	0.9848	0.9837	0.9857	0.9848
	MSE	0.9559	1.2060	0.8273	1.0539
Yolo v11En	R2	0.9850	0.9842	0.9846	0.9839
	MSE	0.8994	1.0907	1.1188	1.2928
Proposed method	R2	0.9880	0.9873	0.9880	0.9875
	MSE	0.2258	0.3599	0.2342	0.3596

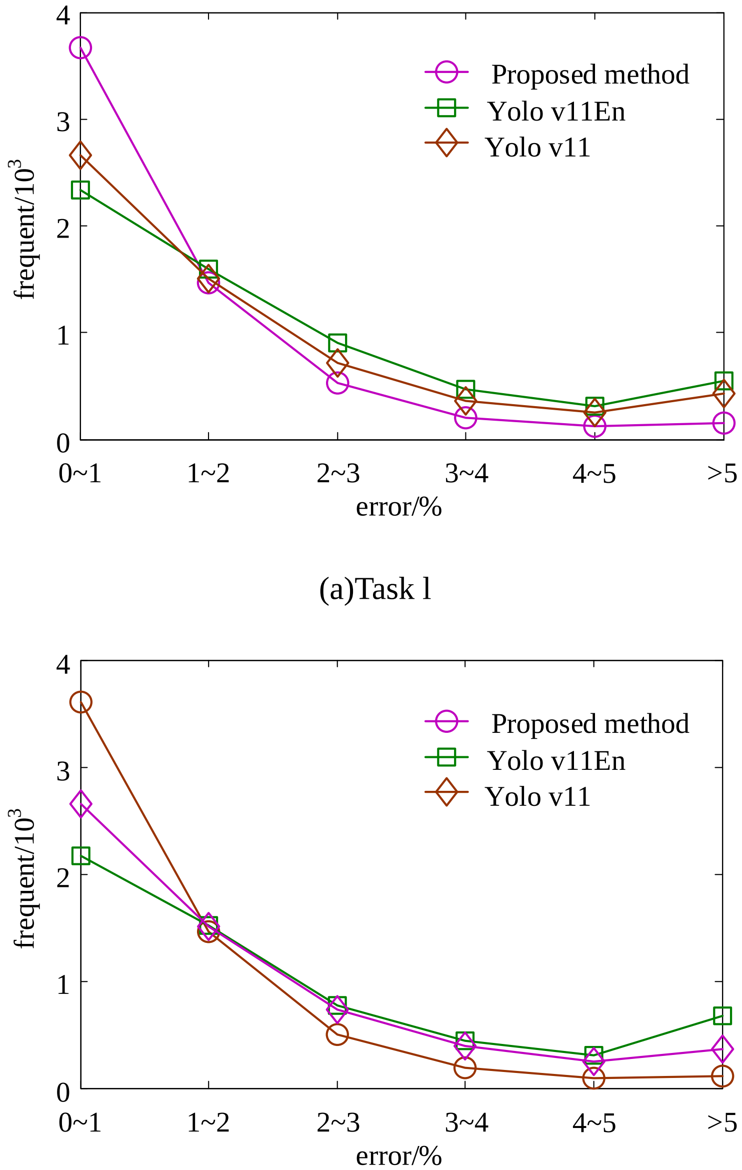
However, in terms of MSE indicators, the three models showed significant differences. In terms of the test set, the Proposed method model performs excellently, with MSEs of 0.3700 (Task 1 test set composite value) and 0.3607 (Task 2 test set composite value), respectively. However, the MSEs of Yolo v11 and Yolo v11En models on the test set are both greater than 1. In specific comparison, compared to the Yolo v11 model, the MSE of the Proposed method model on the left and right main landing gear vertical load test sets (corresponding to Task 1 and Task 2 test sets) decreased by 75.50% (from 1.2060 to 0.3599 in Task 1) and 66.13% (from 1.0539 to 0.3596 in Task 2), respectively; Compared to the Yolo v11En model, it decreased by 73.98% (from 1.0907 to 0.3599 in Task 1) and 72.34% (from 1.2928 to 0.3596 in Task 2), respectively.

Further analysis of the MSE difference between the training and testing sets revealed that the Yolo v11 model had a MSE difference of 0.9559-1.2060=-0.2501 (absolute value 0.2501) in Task 1 and 0.8273-1.0539=-0.2266 (absolute value 0.2266) in Task 2; The Yolo v11En model has a difference of 0.8994-1.0907=-0.1913 (absolute value 0.1913) in Task 1, and 1.1188-1.2928=-0.174 (absolute value 0.174) in Task 2; The difference between the proposed method model in Task 1 is 0.2258-0.3599=-0.1341 (absolute value 0.1341), and in Task 2 it is 0.2342-0.3596=-0.1254 (absolute value 0.1254). This indicates that the proposed method model has smaller performance fluctuations and stronger stability on both the training and testing sets.

In summary, the proposed method model not only has the smallest MSE value and is close to 0, but also reduces MSE by more than 66% on the test set. Moreover, it has better stability and can better capture the complex relationships between different variables, achieving more accurate prediction of load data. It has obvious advantages in the model comparison involved in this experiment.

The distribution of relative errors in the predicted values of the three models is shown in **Figure 6**. Relative error is an indicator that measures the difference between predicted values and true values, and can intuitively reflect the credibility of predicted values.

From **Figure 6** (a), it can be seen that for the Proposed method model, 85.16% of the sample load prediction errors are controlled within 2%. Within the same error range, the sample proportion of Yolo v11 model is 70.13%, while that of Yolo v11En model is 64.65%. Similarly, from **Figure 6** (b), it can be seen that for the Proposed method model, 84.73% of the sample load prediction errors are controlled within 2%, the Yolo v11 model has a sample proportion of 69.48%, and the Yolo v11En model has a sample proportion of 61.32%.



(a)Task l

(b) Task 2

Figure 6: Distribution of relative errors in predicted values of different models

The average relative errors of the three models are shown in **Table 2**. It can be seen that the proposed method model has an average prediction error of 1.21% and 1.19% for the vertical load on the left and right main landing gear, respectively, which is significantly better than the other two models. This indicates that the proposed method model has the highest accuracy in predicting landing gear load. From this, it can be seen that the landing gear load prediction model based on the Proposed method model has good reliability.

From the data in **Table 2**, it can be intuitively seen that in Task 1 (vertical load on the left main landing gear), the average relative error of the Yolo v11 model is 2.029%, the Yolo v11En model reaches 2.178%, and the Proposed method model is only 1.206%. This means that in the vertical load prediction of the left main landing gear, the Proposed method model has reduced the error by (2.029-1.206) ÷ 2.029 × 100% ≈ 40.56% compared to the Yolo v11 model; Compared to the Yolo v11En model, the error has been reduced by (2.178-1.206) ÷ 2.178 × 100% ≈ 44.63%. In Task 2 (vertical load on the right main landing gear), the average relative error of the Yolo v11 model is 1.887%, the Yolo v11En model is 2.346%, and the Proposed method model is 1.184%. Similarly, compared to the Yolo v11 model, the Proposed method model reduces the error by (1.887-1.184) ÷ 1.887 × 100% ≈ 37.26%; Compared to the Yolo v11En model, the error has been reduced by (2.346-1.184) ÷ 2.346 × 100% ≈ 49.53%.

Table 2: Average relative error of three models

Model	Average error/%	
	Task l	Task 2
Yolo v11	2.029	1.887
Yolo v11En	2.178	2.346
Proposed method	1.206	1.184

Based on the data from both tasks, the proposed method model has an average prediction error of 1.21% (approximately 1.206%) and 1.19% (approximately 1.184%) for the vertical load on the left and right main landing gear, respectively, which are significantly lower than the Yolo v11 and Yolo v11En models. This fully demonstrates that the Proposed method model can more accurately capture data features when processing landing gear load prediction tasks, effectively reducing the deviation between predicted values and true values, and achieving the highest accuracy in landing gear load prediction.

Based on the comprehensive and detailed data comparison analysis above, we have sufficient reasons to conclude that the landing gear landing load prediction model based on the Proposed method model, with its significantly lower average relative error compared to the other two models, demonstrates good reliability and has higher value and potential in practical applications.

6 Conclusion

The core issue of this study is the accurate prediction of landing load on aircraft landing gear, with the goal of implementing a maintenance strategy for the landing gear based on the situation through accurate prediction, thereby ensuring the safety and security of the flight process. Given the inefficient resource utilization and potential safety risks caused by the traditional "safe life" design concept, as well as the complexity and high resource consumption in the CAE simulation model construction process, and the unique advantages of machine learning technology in load prediction, this study has decided to rely on actual test flight data of a specific aircraft model for in-depth exploration. In the data preprocessing stage, a systematic data cleaning and feature dimensionality reduction operation was performed on the collected 220956 sample data (including 209956 for model training and 11000 for model testing). Specifically, Savitzky Golay filters are used to smooth the raw load data collected by sensors to eliminate noise interference; Subsequently, the features were preliminarily screened using mutual information method, and redundant features were further removed by combining variance threshold; Finally, the Pearson correlation coefficient method was used to address the issue of multicollinearity between features, and 13 key flight parameters were ultimately determined as input features for the model. At the level of model construction, this study innovatively introduced the Yolo v11 algorithm model as the basic framework, and optimized and upgraded it by integrating advanced technologies such as CBAM attention mechanism, C3Chost module, and DyHead object detection, successfully constructing a landing gear landing load prediction model based on the improved Yolo v11 algorithm. In the experimental stage, the improved model was compared and analyzed with the original Yolo v11 model and Yolo v11En model, and the model performance was comprehensively evaluated using multiple indicators such as R^2, MSE, and average relative error. The experimental results show that the three models perform similarly on the R^2 index, and there is no significant overfitting phenomenon observed; However, in terms of MSE and average relative error metrics, the proposed method in this study demonstrated significant advantages. Its MSE value on the test set decreased by over 66%, and the average prediction errors were controlled at lower levels of 1.21% and 1.19%, respectively. Additionally, the MSE difference between the training and testing sets was smaller, indicating that the model has stronger stability and reliability. This series of data fully demonstrates the outstanding performance of the model in prediction accuracy, stability, and reliability, laying a solid foundation for its promotion in practical applications.

Looking towards the future, this study intends to advance the work from the following dimensions, aiming to comprehensively enhance the application efficiency and theoretical depth of the landing gear load prediction model:

At the level of model optimization, we will focus on iterative upgrades of deep learning techniques. Specifically, we plan to introduce transfer learning strategies by reusing pre trained weights from annotated datasets in the aerospace field, breaking through the bottleneck of model training in small sample scenarios and achieving a dual improvement in convergence speed and prediction accuracy. At the same time, efforts are being made to construct a reinforcement learning driven dynamic prediction framework that enables the model to autonomously optimize its prediction logic based on real-time flight parameters such as airspeed and angle of attack, enhancing its adaptability to atypical operating conditions. In addition, the plan is to use automatic machine learning (AutoML) technology to build a hyperparameter optimization pipeline, replacing manual parameter tuning with algorithms such as Bayesian optimization, significantly improving research and development efficiency while ensuring model performance.

In terms of data engineering, we will focus on building a multi-source heterogeneous data ecosystem. In addition to expanding the existing dataset to cover aircraft models and extreme working conditions (such as crosswind landing and asymmetric braking), the focus is on integrating three new types of data sources: firstly, deploying high-precision structural health monitoring (SHM) systems to collect vibration time-frequency characteristics of key components of landing gear; Secondly, integrate environmental perception data, including parameters such as runway friction coefficient and atmospheric temperature and humidity gradient; Thirdly, access the Flight Operations Record (FOQA) database to extract the correlation features between pilot control inputs and payload responses. In response to the challenge of high annotation costs, we plan to develop a semi supervised representation learning framework based on contrastive learning. By designing data augmentation strategies and measuring learning objectives, we aim to fully explore the potential value of unlabeled data.

Author's Profile

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