APPLICATION OF CONVOLUTIONAL NEURAL NETWORKS IN DETERMINING THE VELOCITY AND PRESSURE FIELDS AROUND AIRFOIL MODELS

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Abstract

The article constructs a convolutional neural network for predicting pressure and velocity fields around a two-dimensional aircraft wing model (airfoil model). Training data is computed using the Reynolds-averaged method, then extracted, focusing on the flow around the wing. Input data includes geometric parameters, airfoil inlet velocity, and output data includes pressure field and flow velocity around the airfoil. The convolutional neural network is based on improving the U-Net network model, commonly used in medical applications. The results show that the convolutional neural network accurately predicts flow around the airfoil, with an average error below 3%. Therefore, this network can be used and further developed to predict flow around the wing. Results related to pressure distribution, velocity, and method error are presented and discussed in the study.

Keywords: Neural Networks, Velocity and Pressure Fields, Airfoil

1. Introduction

The aircraft wing is the primary component generating lift, enabling the aircraft to operate in atmosphere. Along with the advancement of aviation and computational techniques over the past 100 years, the wing database system has been built and improved. Some notable examples include the NACA wing system, the Xfoil software [1], which allows the output of lift, drag, and pressure distribution data on the wing surface in short time. More accurate methods, such as using software to solve finite volume problems, allow for the distribution of pressure, velocity, and friction around the wing surface. These are traditional approaches based on mathematical equations and solving problems by discretizing computational space [2], [3],[7].

Today, artificial neural networks have been widely applied in scientific and engineering fields. With large training datasets, the results obtained from neural networks have shown good predictions with small errors compared to traditional methods. In aerodynamics, artificial neural networks are used to predict lift and drag values of models. Global networks like convolutional neural networks allow for the distribution of pressure and velocity fields around models with small errors. In this method, training and testing data are generated from traditional computational methods, then rearranged into four-dimensional arrays. The data passes through convolutional neural networks to extract features, which are then reconstructed into pressure and velocity fields. Through the training process, the network parameters are adjusted to provide pressure and velocity field results close to the original data. The network parameters are formed. Some networks developed for this task include Flow Net for optical flow, U-Net for medical applications [4],[6]. However, artificial neural networks, besides mathematical properties, also have architectural or artistic characteristics. Therefore, the results vary depending on the choice of convolutional network architecture.

In this study, we propose modifications to the structure of the conventional U-Net network to serve the extraction of pressure and velocity fields around a two-dimensional aircraft wing model (airfoil). Training and testing data include 400 airfoil cases with different shapes and flow conditions. The results of training on the U-Net network show that this model allows accurate prediction of velocity and pressure field features with a common error of less than 3%. Therefore, the networks can be used in computing flow features around physical models.

2. Convolutional Neural Network Diagram and Training Data

2.1. Convolutional Neural Network Diagram

U-Net Convolutional Neural Network is a network architecture used in the field of image processing, particularly for segmentation tasks. This architecture is designed to retain high-level information (learned from convolutional layers) while also maintaining specific positional information (learned from pooling layers). U-Net is typically divided into two main parts: the encoder and the decoder. The encoder uses convolutional layers to extract information from the input image and applies pooling layers to reduce the feature size while retaining important information. Conversely, the decoder uses transposed convolutional layers to reconstruct the image with high resolution and combines information from the corresponding encoding layers through skip connections to recreate specific objects. U-Net has demonstrated good performance in various applications, including cell segmentation in medical images, object recognition in images, and many other tasks. The unique structure of U-Net allows it to retain both high-level and positional information, making it a popular choice for tasks that require both detailed and positional information of objects. The output results depend on the number of layers in the U-Net. For the airfoil models, this study uses a U-Net with three input-output layers. The network input is modified to be a three-dimensional matrix of size 128×128×3. The first two dimensions represent the image size, and the third dimension sequentially represents the model's geometry, the input velocity in the x direction, and the input velocity in the y direction. Each convolutional layer is followed by a ReLU layer, and the final convolutional layer is followed by a Max Pooling layer. Initially, the U-Net network was used for image segmentation. Therefore, the output parameter is changed to a three-dimensional matrix of size 128×128×3, where the third dimension sequentially represents the pressure field, the output velocity in the *x* direction, and the output velocity in the y direction. The network includes 7.6 million parameters. The structure of the U-Net and its parameters are presented in Figure 1. The network structure and training process are built using MATLAB software.

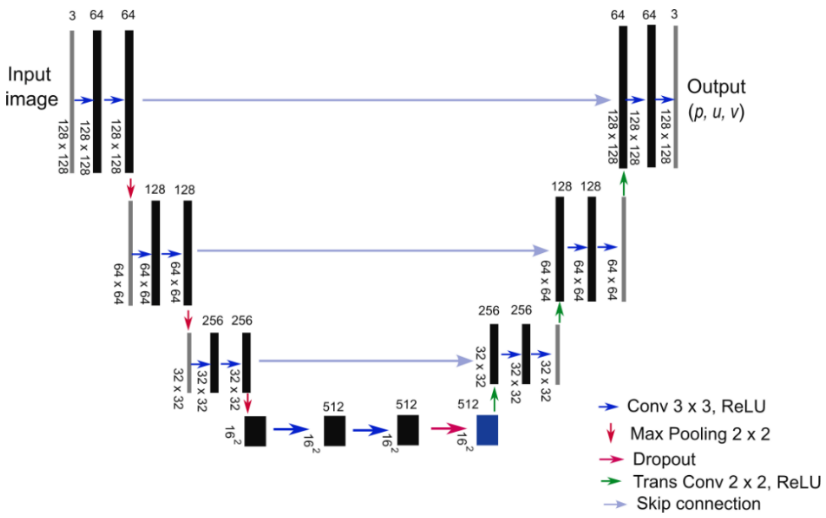

Figure 1. Diagram of the 3-layer U-Net network

2.2. Training Data

The training data used in this study is taken from the dataset published by Thuerey and colleagues [5]. Specifically, the Reynolds-Averaged Navier-Stokes (RANS) method with the Spalart-Allmaras turbulence model is used. Calculations are performed in the OpenFoam environment. The geometric features and the flow around the model are cropped to a size of 128 × 128 pixels to facilitate the training process. A total of 400 data sets are used for training. An example of the training data field is shown in Figure 2. It includes the geometry, the free stream in *x* and *y* directions, the results of pressure fields, velocity fields. All data of the input and output has the same size of 128 × 128 pixels.

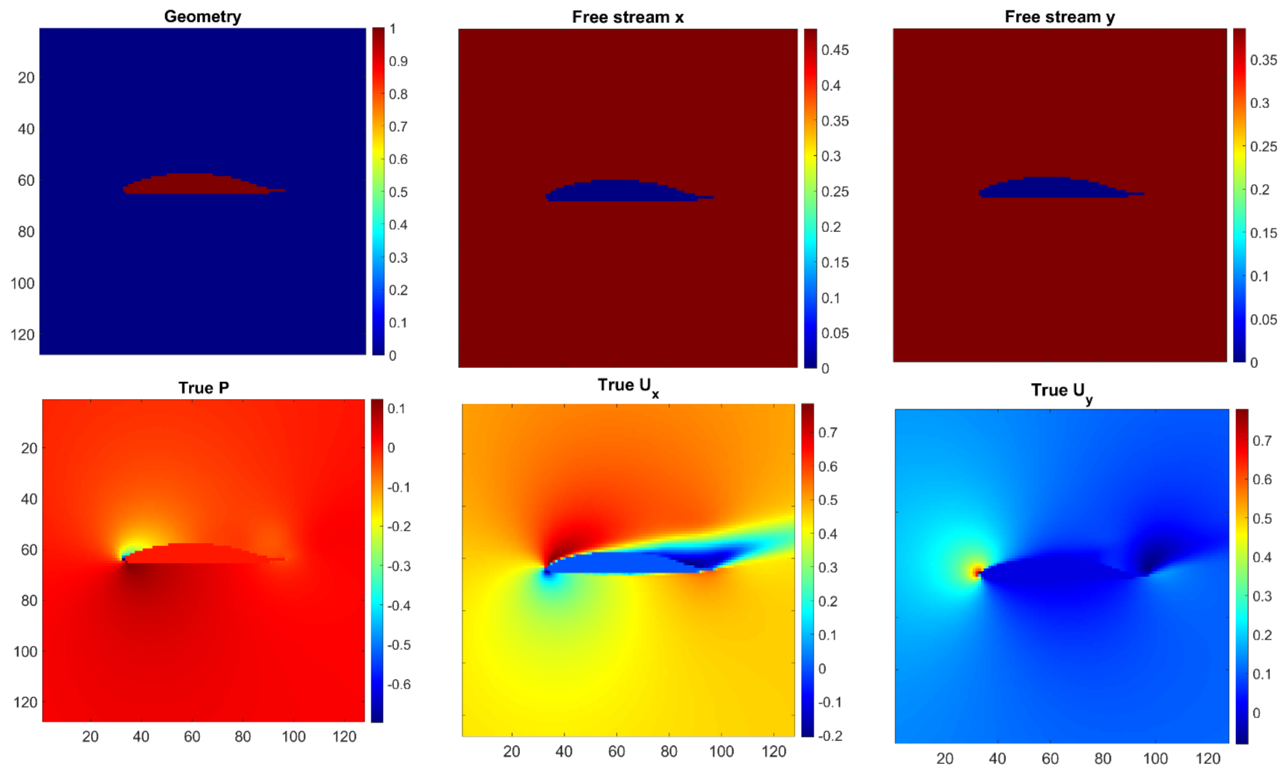

Figure 2. Training data for the training process

2.3. Training Model

The three-layer U-Net network described in section 2.1 is used for the training process. The airfoil data is divided into 80% for training and 20% for testing. The training data is divided into minibatches with a size of 10. The loss function is calculated as the average error of the pressure field and velocities during training with the standard data. A total of 100 epochs are performed for the training process. The adaptive moment estimation (Adam) algorithm is used. The learning rate is fixed at 0.001. It should be noted that the learning rate can affect the convergence of the problem. However, calculations in this study show that reducing or changing the learning rate around the chosen parameter does not significantly change the loss function. The training process is performed using MATLAB software in graphical card (GPU).

3. Results and Discussion

3.1. Training Error

Figure 3 shows the changes in the loss function over the number of epochs. The loss function decreases rapidly at the beginning and gradually decreases up to 3000 iterations. However, when further increasing the number of iterations, the results change little and converge to a value of 0.03. The loss error is small, and the training results for the pressure and velocity fields can be obtained with small errors.

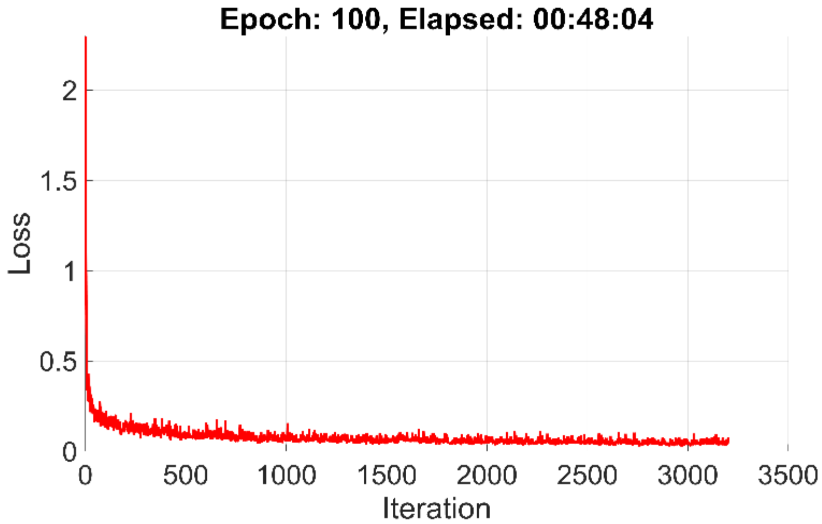

Figure 3. Changes in the loss function over iterations

Figure 4 shows the average error results of the test data. Here, 80 test data sets are calculated. The average error of the calculations is less than 3% for both the pressure field and velocities. However, in some cases, the error increases to 6% or 8%. This can be explained by the fact that when changing the angle of attack, the flow field around the model becomes complex, and thus the error tends to increase. However, the average error is small, indicating that the method is effective in predicting the flow field around the model.

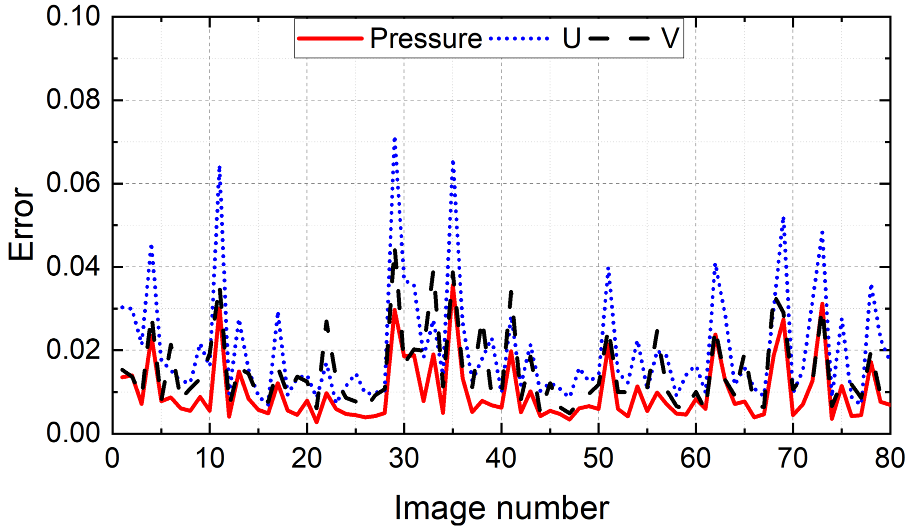

Figure 4. Changes in error over test data

3.2. Training Results

Figure 5 shows the training accuracy, training results, and the airfoil model for two different cases after 100 epochs. In both cases, the training results predict the pressure and velocity fields around the model quite accurately. For example, in case a), the low-pressure and low-velocity region below the airfoil can be described quite accurately from the training. Similarly, the high-velocity region above the model can be described relatively accurately through training. For the highly curved airfoil shown in case b), similar results are obtained from the training. However, compared to numerical simulation calculations, the training results show less smoothness, especially in the pressure field and velocity field v (Figure 5a). This can be explained by the fact that the training model considers each pixel individually and lacks mathematical connections between neighboring pixels.

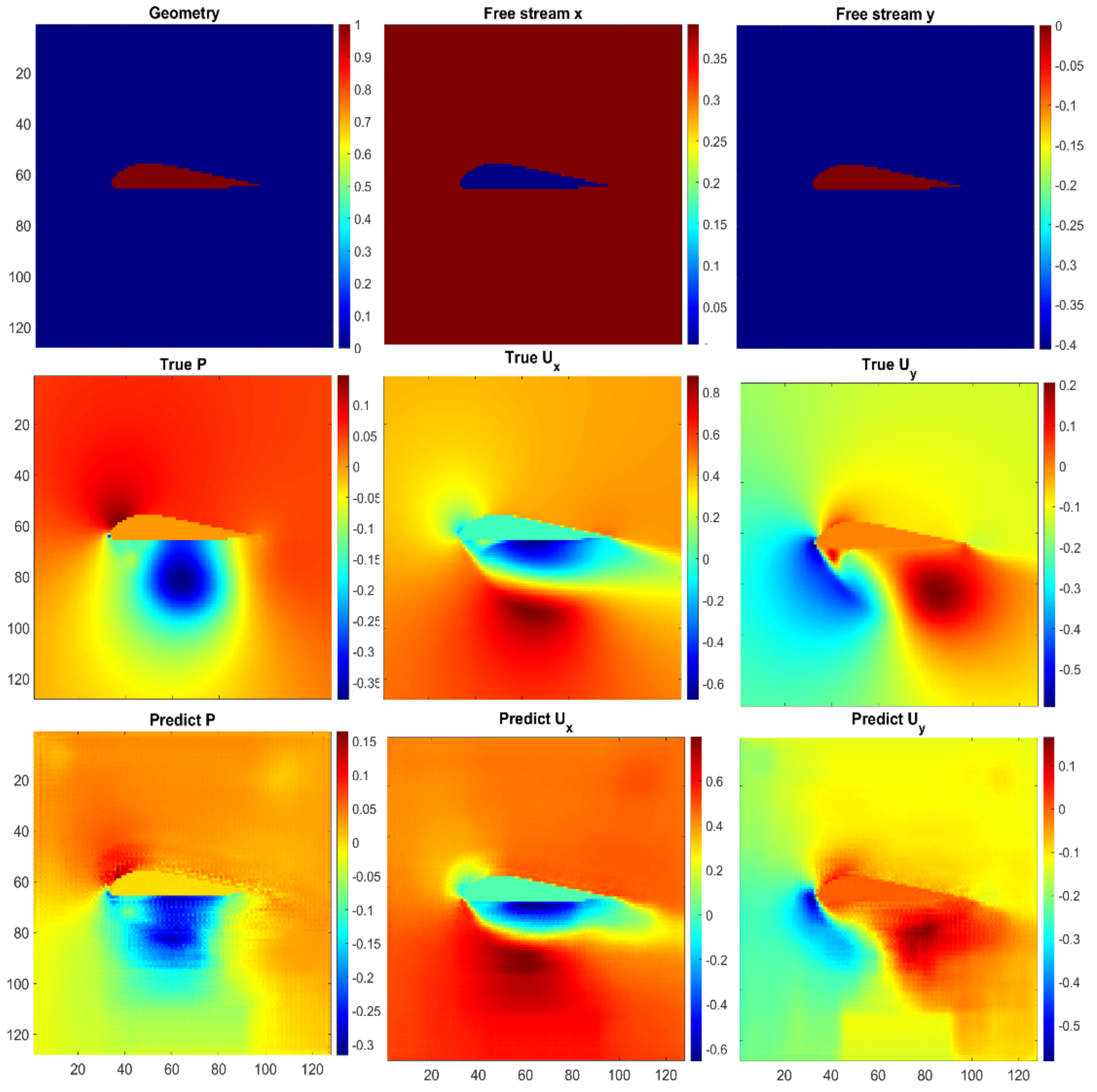

Figure 5 (a). Training results

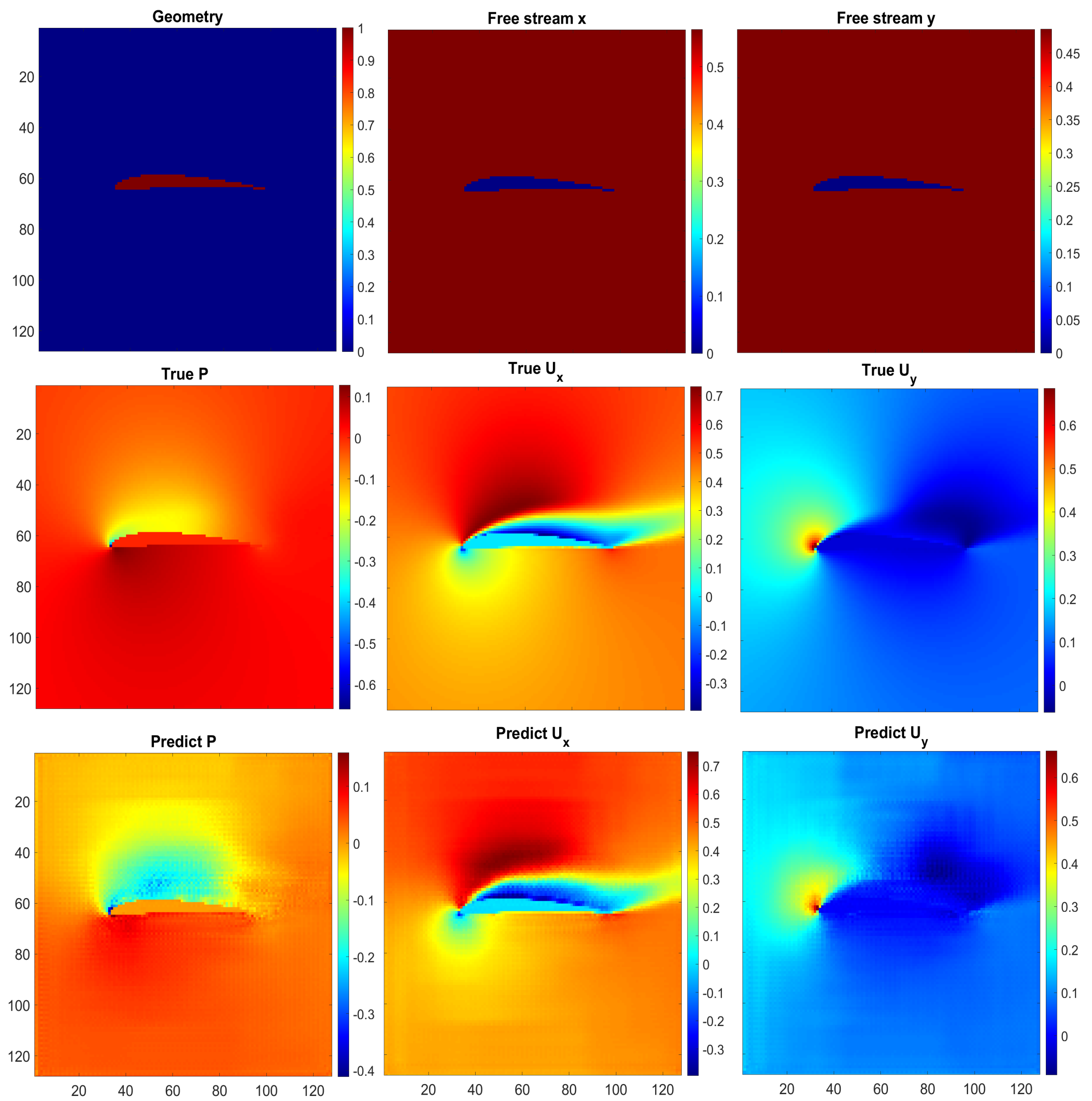

Figure 5 (b). Training results

To further evaluate the error, Figure 6 shows the difference between the pressure and velocity fields between the training model and the standard results from numerical simulation for one airfoil case. In the regions far from the model, the error is small. The error tends to increase when approaching the model. This can be explained by the sudden changes in aerodynamic and geometric parameters at these locations. Additionally, some errors appear along certain streamlines due to the sudden changes in the velocity field. Therefore, further research needs to be conducted to improve the accuracy around the model.

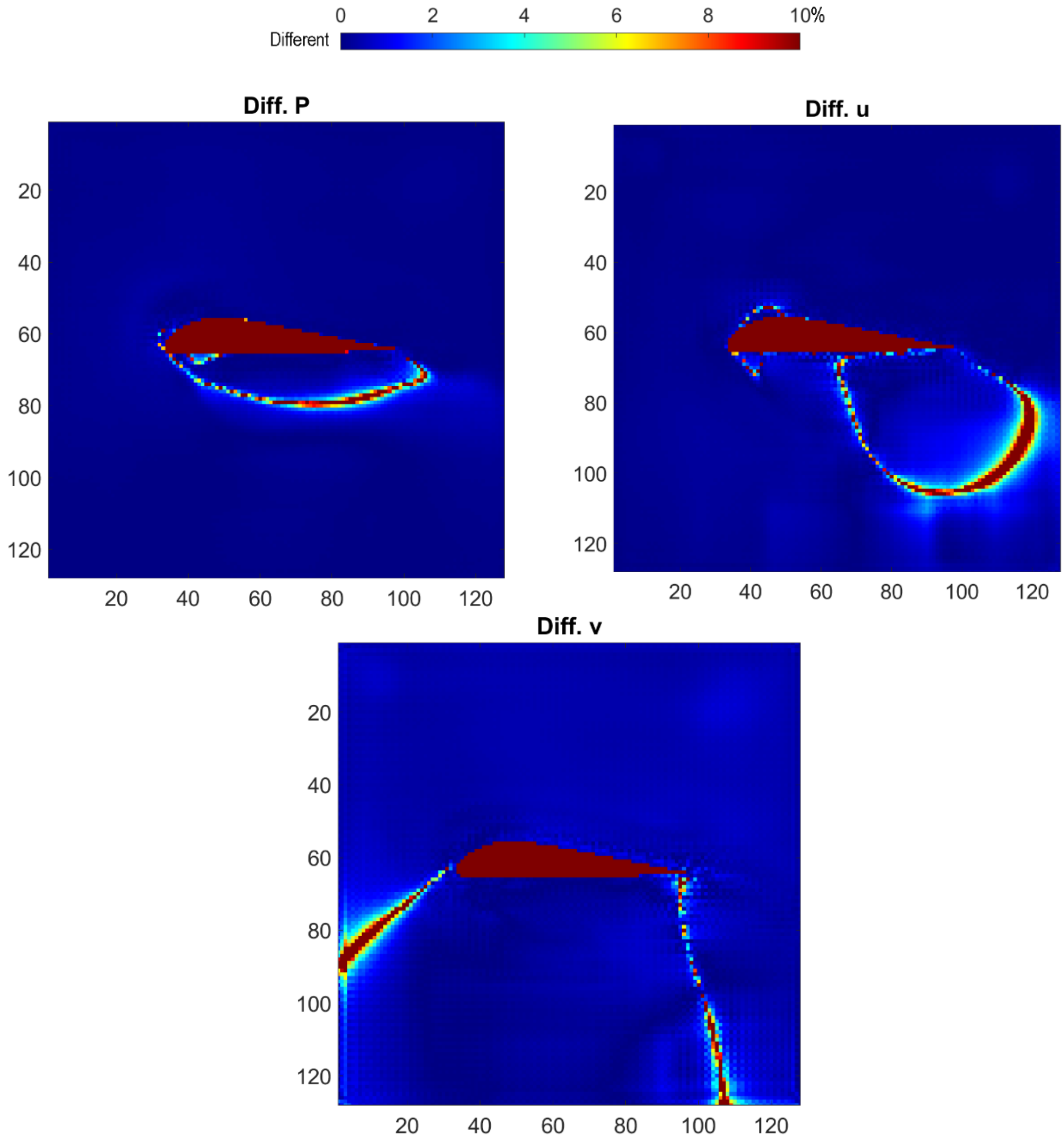

Figure 6. Error between numerical simulation and training results for one airfoil case

3.3. Discussion

The results for the airfoil show that the average error of the pressure and velocity fields is less than 3%. Although the error is acceptable, there are questions about whether the error can be further reduced. Clearly, increasing the training and test data can help reduce the calculation error. However, increasing the training data significantly increases computer resources, which is relatively complex under conditions in Vietnam. Moreover, improving the artificial neural network can help reduce errors. However, in our studies, using 4 or 5 layers of the U-Net network does not significantly reduce the calculation error, although the network parameters increase. Other types of artificial neural networks, such as Flownet, or entirely new networks can be used to reduce calculation errors. The second question is the accuracy of the pressure distribution on the model surface when using this type of artificial neural network. Although some other networks can be used to increase the accuracy of the pressure field distribution prediction, the artificial neural network does not yet represent the physical constraints of the flow, such as the continuity of the velocity and pressure fields. Therefore, physical constraints can be incorporated into the input to increase the model's accuracy. These questions will be specifically answered in our future studies.

4. Conclusion

In this study, a convolutional neural network is built to reproduce the flow around an airplane wing model. The training data is constructed from solving the Navier-Stokes equations using the RANS method. Although the training model is relatively simple, the number of hidden parameters in the neural network is large. The training results show a certain fit and a small error between the training data and the simulation calculations. Therefore, the results of this study can be used to predict the main characteristics of the pressure and velocity fields around the model, serving the optimization process of the airplane wing shape in specific operating conditions. However, the model still needs improvement. Additionally, helping the machine learning model understand the physical phenomena of the flow is a complex issue that needs to be addressed in future studies.

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7. Copyright Statement

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