2D Fluid Flows Prediction Based on U-Net Architecture

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***Abstract*—Computational fluid dynamics (CFD) solvers provide helpful components and amenities for industrial development and the advancement of fluid flow simulations. Nevertheless, CFD solvers are not advantageous since iterative simulations require high computational resources and enormous memory for complex calculations. The deep neural network-based CFD data-driven learning method eliminates these constraints by lowering the compensation between model complicatedness and precision. In this paper, we present the feasibility of predicting fluid flow velocity fields based on CFD using U-Net architecture, a subdomain of deep learning. The experimental results show that the U-Net architecture can predict fluid flow with a total loss of 0.2223, a validation loss of 0.2728, and an accuracy of 86% from our private dataset. Our U-Net model can be used to predict fluid flows, which has been proven.**

***Index Terms*—CFD, Laminar Flow, Deep Learning, Convolutional Neural Networks, U-Net Architecture**

I. Introduction

Energy use forecasting and thermal performance improvement rely on building energy simulations. Some building energy modeling systems can thoroughly examine a year's mechanical design performance and energy consumption data for the target system [1]. Calculations are performed using computational fluid dynamics (CFD) research to show the physical relations of fluid flow and obstacles inside the building with covers described by predetermined boundary constraints. The Navier-Stokes fluid flow equations are an example of a partial differential equation that can be solved via this examination process. This study emphasizes non-uniform steady laminar flow estimation [2].

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In certain circumstances, such as engineering functions, the high expense of CFD simulations may be justified. For example, suppose the Reynolds number (the association between viscous forces and inertial) is sufficiently low. In that case, the flow intention is laminar, meaning that the fluid particles travel along similar layers with no cross-currents oblique to the flow path, as seen in Figure 1. In addition, the issues can be solved as a non-uniform steady laminar flow if the flow achieves a state in which any particular effects, such as the velocity and pressure fields, change across the region [14]. Additionally, using numerical resolution approaches, a trained neural network (NN) can reduce processing costs. In order to unravel and forecast flow, for instance, using extensive eddy calculations for Reynolds-averaged Navier-Stokes (RANS) and simulation, numerous NN models have been developed [3].

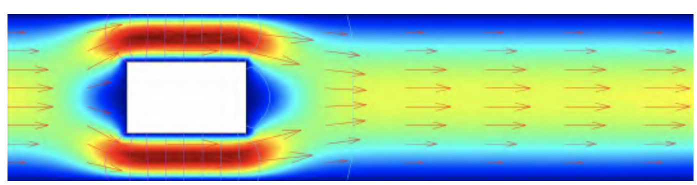


Fig. 1: Sample a non-uniform steady laminar fluid flow for 2D geometry. The white rectangle depicts the obstacle. The pointers indicate the laminar flow's velocity field.

The method used in this paper deploys deep learning techniques to CFD by directly calculating the necessary fluid properties. The U-Net model utilized in this study was used to modify the CNN method, originally employed in biomedical vision segmentation [4].

There are six primary sections to this paper. Related work is presented in Section II. The dataset that discusses the signed distance function (SDF) is explained in Section III. The U-Net model architecture used in this study is presented in Section IV. The total loss and validation loss are discussed in Section V, while the conclusion and future work are discussed in Section VI.

II. Related Work

Deep learning has been implemented in a number of ways to build CFD predictions. Masuda et al. [5] have combined CNN and LSTM, called ConvLSTM. As noise builds up using the predicted data as input, an unoriginal image, like white, is finally produced. ConvLSTM can predict using physically derived physical parameters and pictured images. However, the experiment was conducted with a small training dataset, generating a weak model against noise and overfitting. CFD-CNN was used by Yan et al. [6] to simulate the concentration field of a rosette buoyancy jet using 20 different Froude number cases. Convolutional neural networks (CNNs), which are used for design classification, object distinction, and object detection, can use a variety of neural networks and learning methods, and their capacity for generalization is significantly improved. Comparing CFD-CNN to multigene genetic programming, the former can operate at a higher rate and with more precision. After all, the CFD-CNN experiment needs more data to enhance and extend the model's performance.

Long Short-Term Memory (LSTM) model was used by Mohan et al. [8] and has been shown to have enormous potential for modeling temporal dynamics of turbulence with complex sequential data. Although LSTM can deliver precise prediction, it was observed that when the horizon was extended, accuracy began to decline. On the other hand, Qui et al. [9] have implemented BiLSTM in combination with the CNN model to address the issues with conventional numerical simulation techniques, which are time and resource-intensive in the CFD method. Compared to the single-LSTM model, the BiLSTM model can better consider the influence of each attribute point before and after attributes.

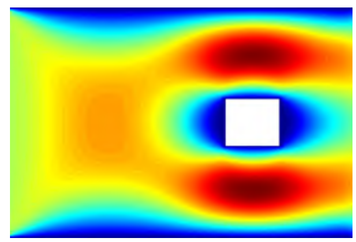
By using a fusion convolutional neural network (CNN), Jin et al. [7] propose predicting the velocity field about a circular cylinder using the pressure field surrounding the cylinder as input. Fusion CNN consists of the max pooling layer-implemented paths (i.e., two paths with a pooling layer and one without a pooling) and the paths without a pooling layer-implemented paths. This type of architecture can store exact spatial-temporal data and features resilient to minor translations in the spatial-temporal series of pressure variations on the cylinder. The time series of pressure fluctuation on the cylinder surface is translated into a spatial-temporal topology resembling a grid to be used as the CNN's input. However, the model can only be trained to recognize inherent properties stored in the data.

To overcome the disadvantages mentioned above, we have implemented a U-Net model architecture to make CFD prediction, which is fast and more reliable for proceeding with fewer images than a convolutional neural network (CNN). The implementation of the Deep Learning model with U-Net architecture to predict fluid flow indoors based on CFD is described in this work.

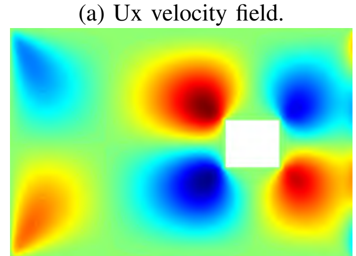
III. Dataset

A. Numerical Data Simulations

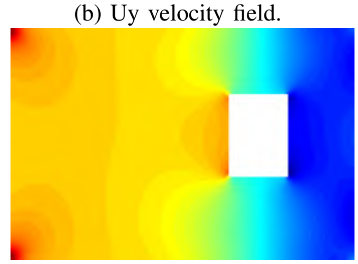
This study used numerical simulations to generate training and testing samples for the network under consideration. These simulations were carried out using the FEAtool commercial software application [10] to get input as the sample dataset shown in Figure 2.



(a) Ux velocity field.



(b) Uy velocity field.



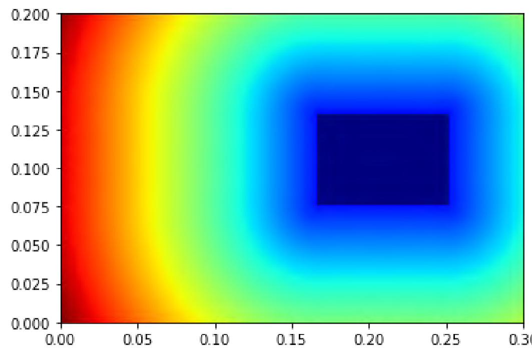
(c) Pressure field.

Fig. 2: Sample images of Ux and Uy for velocity fields and Pressure fields.

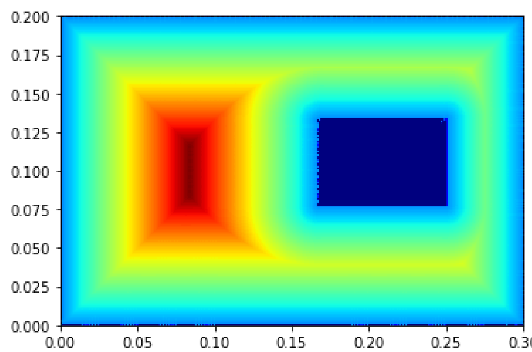
The MATLAB Compiler Runtime (MCR) is necessary for the m-script programming features used in the FEATool Multi-physics software toolkit to execute and comprehend the codes. This study emulated a rectangle-shaped obstacle and a two-dimensional computational domain.

B. Signed Distance Function (SDF)

The Signed Distance Function (SDF) is the geometry representation in this article. A closed geometry shape's nearest boundary can be determined at any location in the grid using the SDF function. Depending on whether a point is within (negative) or outside (positive) of the form, the sign of each number changes [2]. There are 300 instances of each Ux, Uy, P, Grid, and Boundary data in the train and test datasets used in this study, with Ux and Uy being the desired results for velocity fields, and P for pressure fields, respectively. The sample of the SDF image represents the boundary and grid depicted in Figure 3.



(a) SDF boundary image.



(b) SDF grid image.

Fig. 3: SDF boundary and grid images.

IV. Methodology

Figure 4 details the U-Net design architecture. A U-Net design's primary framework consists of two tracks, a contracting track on the left track and an expansive track on the right track [11].

The contracting path is the initial track, which uses a conventional CNN design. Each block of the contracting path consists of a ReLU activation component, a max-pooling layer, and two consecutive 3×3 convolutions. The extended track contains several variations of this arrangement, each of which uses 2×2 up-convolution to upsample the feature map. The upsampled feature map is then cropped and joined to the matching layer's feature map in the contracting path. The segmented image is created after the feature map has been condensed to the required number of channels using an extra 1×1 convolution. Because they provide the least amount of contextual data image, the pixels' margins must be clipped. This creates a network with a u-shape appearance and, more importantly, reproduces contextual data images throughout the structure, allowing it to segregate things in one area using context from a broader overlapping region [12].

In this research, each process encompasses two convolutional layers. The image size reduction from 200×300 to 196×296 results from padding issues, even though this performance employs padding= "same," as indicated by the green arrow pointing downward in Figure 4. The image will be enlarged to its full size on the contrasting side along the expansive route.

An upsampling technique is called transposed convolution. The skip connections enable the transfer of unprocessed data from layers on the downsampling path to the upsampling path (the copy and crop procedures in Figure 3). Convolution layer output from the downsampling path is incorporated with features created from the upsampled input to create the upsampling path [13]. This path can enlarge images, as the image used in this study, its size extended from 4×18 to 17×30 and then concatenated with a similar image from the contracting path to create an image with the dimensions of 13×26. The process of U-Net is done following the transposed convolution until the image is returned to the original size 200×300. Here, data from earlier layers are combined to produce a more precise prediction. This study shows how well such networks may be utilized to map coupled velocity-pressure field geometries to steady-state fluid flow solutions, even though U-Net was first created to segment medical images [14].

V. Results and Analysis

In this study, the U-Net method was trained using a dataset divided into 70% train data and 30% test as the best training/testing ratio to acquire the best performance of the machine learning (ML) models [15]. Besides that, the performance of the training network has been evaluated using the custom loss function, in which we proceed with the predicted values respected to the actual values [16]. At every epoch throughout the training stage, the training result is validated. In this paper, 200 epochs are used, with increasing training epochs, and the training loss gradually reduces in comparison to the validation loss [17] and a learning rate of 0.01 is selected based on the default value, which typically performs for standard multi-layer neural networks [18].

The Adam optimizer was used because it can achieve the quickest confluence time throughout the experiment [19]. The training U-Net technique generated a total loss of 0.2223, with comprise of loss Ux 0.0110, loss Uy 0.0271, and loss Pressure 0.0267, and generated a validation loss of 0.2728 with comprise of validation loss Ux 0.0187, validation loss Uy 0.0291, and validation loss Pressure 0.0304, the U-Net model can represent these modeling processes with small error rates. It was determined that the tiny batch, which was conducted with a single batch size utilized in this study, has a regularizing effect because the noise that small batches add to the updates helps training in avoiding suboptimal local minima [20].

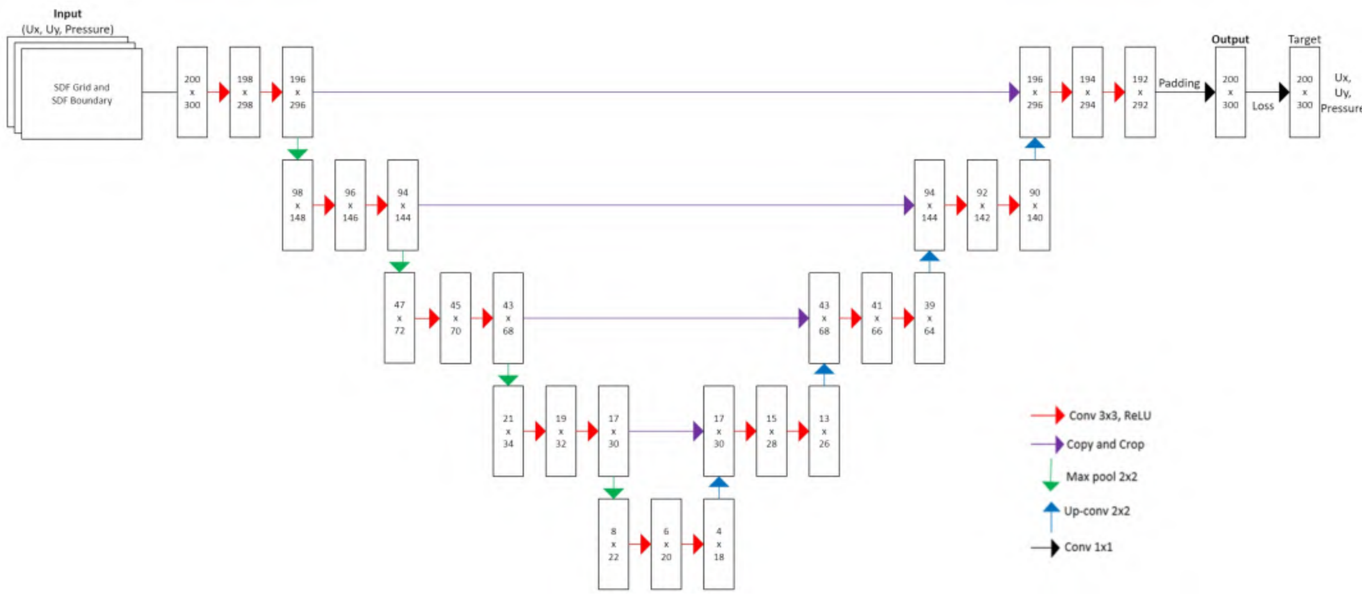
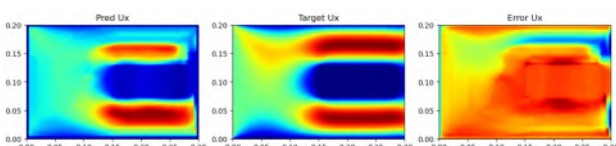
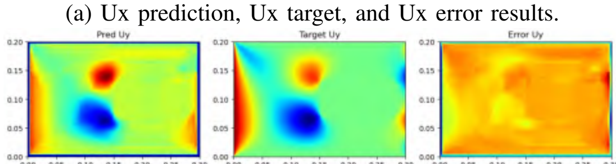


Fig. 4: U-Net architecture for CFD prediction with the contracting path on the left side and expansive path on the right side.

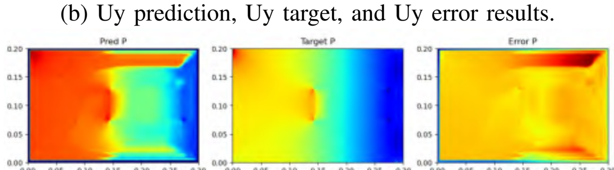
The comparison of predicted and targeted data of the Ux and Uy velocities fields and Pressure components in the field flow is presented in Figure 5. The U-Net network's skip-connections helped our experiment's good accuracy result of 86%. The skip connections help image reconstructions be more precise [14]. Using this U-Net technique allows spatial information to be learned more effectively. When the output of the appropriate encoded section is added, the upsampling's checkerboard distortion is reduced, and the localization information is more effectively retrieved [21].



(a) Ux prediction, Ux target, and Ux error results.



(b) Uy prediction, Uy target, and Uy error results.



(c) Pressure prediction, Pressure target, and Pressure error results.

Fig. 5: Prediction results based on U-Net model architecture.

VI. Conclusion

This work uses a U-Net model architecture to show how field flow prediction based on CFD is implemented. This model predicts airflow in a two-dimensional environment with Ux and Uy for velocity and P for pressure fields. The U-Net approach can predict outcomes with an accuracy of 86%, a total loss of 0.2223, and a validation loss of 0.2728. Future studies must investigate the technique to increase accuracy and reduce loss. Furthermore, by integrating the U-Net model with another model, such as a long short-term memory (LSTM) or bidirectional long short-term memory (BiLSTM), we expect to address the overfitting issue and reduce the loss and validation loss.

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