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Shock Wave Structure and Surface Pressure Prediction Using Deep Learning Model

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Abstract

Obtaining aerodynamic data through wind tunnel tests or CFD calculations requires substantial human, temporal, and financial resources. This study proposes an alternative method for acquiring aerodynamic data using AI(artificial intelligence) models. Two AI models were employed to predict two types of aerodynamic data. The first AI model utilized a U-Net to learn and predict the structure of shock waves from input images without flow. The second AI model, based on LeNet, was trained to predict surface pressure of a test model from images with shock waves. The training data included shadowgraph images and surface pressure data from wind tunnel tests. The validation of the AI model was conducted by using images of an arbitrary shape from wind tunnel test models as input and comparing the output with CFD results. This validation process aimed to assess the predictive capability of the AI models on data that were not part of the training set, thus confirming the generalizability of the AI models. The results indicated that the aerodynamic data predicted by the AI models was considered valid when compared to the CFD data.

Keywords : *SWBLI(Shock Wave-Boundary Layer Interaction), Deep Learning, CNN(Convolution Neural Network), U-Net, LeNet*

Nomenclature

P_0 – Total pressure of storage tube before expansion wave propagates
T_0 – Total temperature of storage tube before expansion wave propagates
P_{1t} – Total pressure of storage tube after expansion wave propagates
T_{1t} – Total temperature of storage tube after expansion wave propagates
M_∞ – Mach number at nozzle exit
P_∞ – Pressure at nozzle exit

1. Introduction

The demand for the development of supersonic and hypersonic aircraft has been on the rise recently. The conventional research process of obtaining aerodynamic data through wind tunnel tests or CFD simulations requires significant temporal, financial, and human resources. Conducting wind tunnel tests, for example, requires the construction of wind tunnel facilities, which is a prerequisite demanding substantial space and time. Furthermore, for each experiment, a new wind tunnel model must be designed, manufactured, and equipped with various measurement devices tailored to the specific aerodynamic data to be obtained. Moreover, the process of wind tunnel testing consumes a significant amount of time, as illustrated in Fig. 1 [1].

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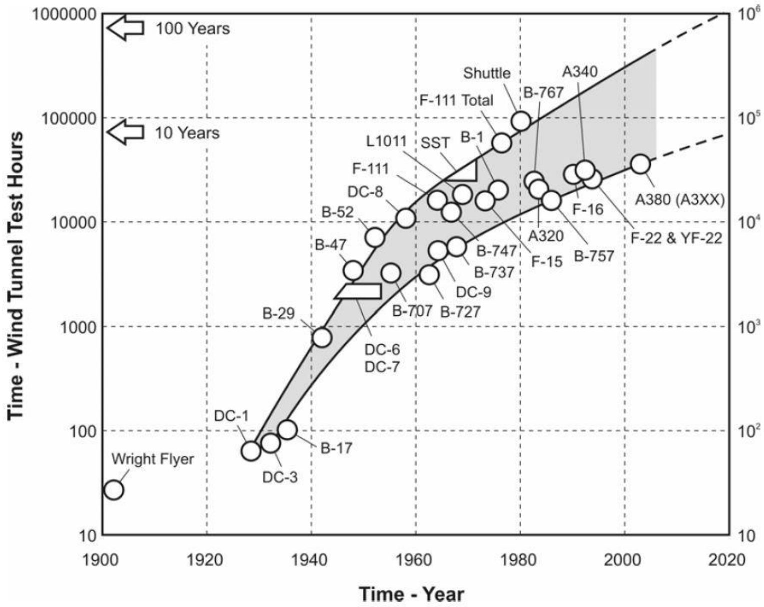

Fig 1. Wind tunnel testing time of new aircraft in the development phase

as a function of aircraft type and year

CFD simulations also demand extensive computing resources, given that generating new grids and conducting compressible 3D flow calculations is a time-consuming process. Therefore, ongoing efforts are being made to enhance the procedure for extracting aerodynamic data more effectively using AI.

Various studies employing AI are actively underway in the aerospace field. Jean et al. conducted a study using satellite images to quantify and predict poverty in five African countries [2]. Y. Afshar et al. developed a machine learning model using the LeNet-5 to train on CFD data. The model takes the shape of an airfoil as input and outputs x-direction velocity (u), y-direction velocity (v), and pressure (p) [3]. Yunfei et al. utilized the Symmetry Neural Network in a Supersonic Cascade Channel to train on CFD data, taking surface pressure values as input and outputting the flow field [4]. Zhixian et al. conducted research using the Fully Convolutional Network (FCN) neural network, training on both CFD data and Jet Actuator experiment data. The model takes the shape of a cylinder as input and outputs the vortex pattern in the wake [5]. Vinothkumar et al. developed a machine learning model using Convolutional Neural Network (CNN) and Multi-Layer Perceptron (MLP) to train on CFD data. The model takes the shape of an airfoil as input and outputs x-direction velocity (u) and y-direction velocity (v) [6].

This study proposes a method to extract two types of aerodynamic data using two AI models. The first AI model was trained on shadowgraph images, both with and without flow, to predict the shape of the shock waves to be generated. The second AI model was trained on shadowgraph images with shock waves and surface pressure data to predict the surface pressure of the wind tunnel test model.

The following sections will be organized as follows: Firstly, details about the wind tunnel tests conducted to acquire data for AI training and the verification of the results will be provided. Subsequently, the content of AI training, the results of AI predictions, and the verification process will be discussed. Finally, the conclusion and discussion will be presented.

2. Conducting Wind Tunnel Tests to Acquire Training Data for AI Training

The shadowgraph data used in AI training and the surface pressure data from the wind tunnel model were obtained through testing the shock wave-boundary layer interaction. Shock wave-boundary layer interaction is a phenomenon occurring during the flight of most supersonic and hypersonic aircraft, either externally around the aircraft or internally within the engine. It involves the interference of shock waves and boundary layers, creating a high-temperature, high-pressure environment and forming complex flow structures. Shock wave-boundary layer interaction is broadly classified into three, as illustrated in Fig. 2 [7].

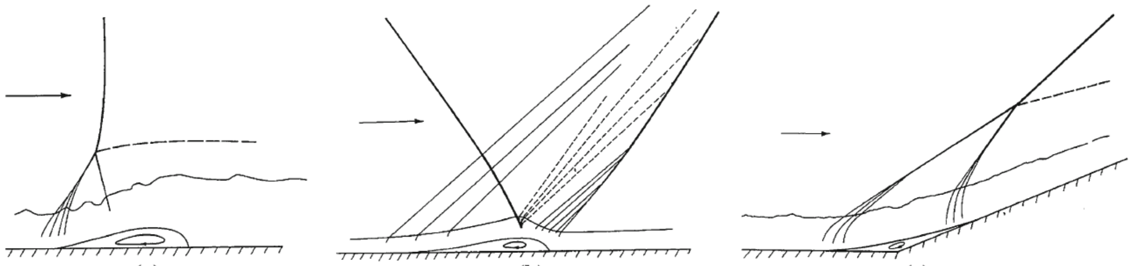

Fig 2. Schematic representation of typical situations where SBLWI is encountered.

In this study, data for Ai training was obtained by testing the interaction of an oblique shock wave and a boundary layer on flat plate.

2.1. Experiment Facility and Wind Tunnel Model

To simulate shock wave-boundary layer interaction, a wedge model was designed to generate an oblique shock wave, and a flat plate model was designed to generate the boundary layer. The wedge model was designed to vary the angle of the oblique shock wave and an orifice was designed to measure pressure along the centerline in the flow direction on the plate. The Wedge Model and Flat Plate are showed in Fig. 3.

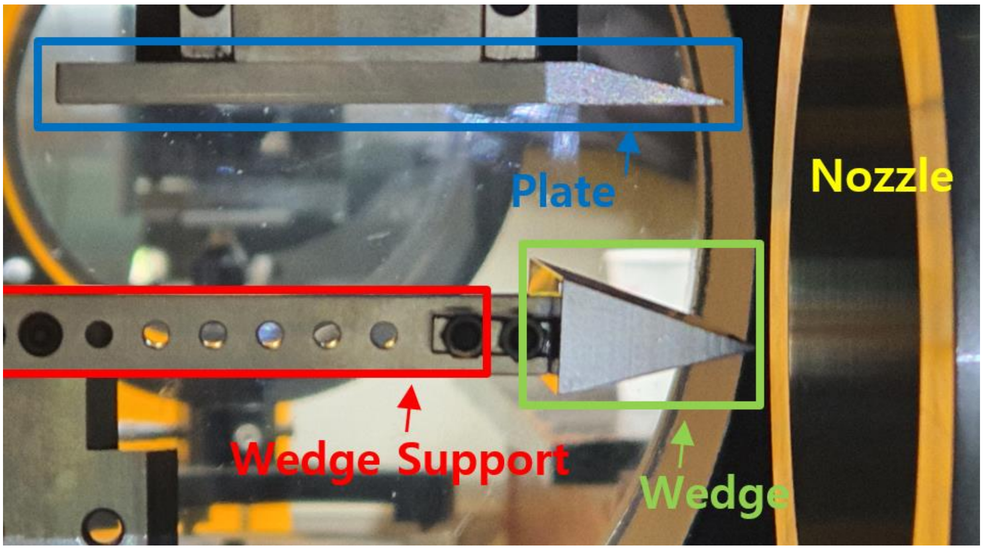

Fig 3. Wedge and Plate model in test section

The wind tunnel used in this study was the Ludwieg Tube at Konkuk University. The Ludwieg Tube is an impulse-type hypersonic wind tunnel operated using a fast-acting valve mechanism. The length of the storage tube is 21m, and the duration time is about 100ms. The conditions of the flow used in the experiments are presented in Tabel 1.

Table 1. Flow condition of wind tunnel testing

	Property	Value
Storage Tube	$P_0(Mpa)$	3 ± 0.6
	$T_0(K)$	301 ± 3
	$P_{1t}(Mpa)$	2.42 ± 0.06
	$T_1(K)$	2.37 ± 0.04
Nozzle Exit	M_∞	4

$P_\infty(\text{kpa})$	15.9

2.2. Experiment data validation

To validate the experiment data, CFD analyses were performed using the in-house code "KFLOW" at Konkuk University. The CFD simulations utilized the 3D compressible Navier-Stokes equations, employing the Reynolds-Averaged Navier-Stokes (RANS) method. The flow condition and numerical techniques employed in the simulations are detailed in Table 2.

Table 2. Flow condition and numerical technique of CFD

Flow Condition	M_∞	4
	$P_\infty(\text{kpa})$	15.9
	$T_\infty(K)$	67
	$Re(m^{-1})$	$1.2E+0.8$
Numerical Technique	Flux Function	ASMU+
	Turbulent Model	$\gamma - Re_\theta$ Transition
	Flow Type	Steady Flow
	Error Tolerance	1.0E-5

3. AI Learning

One challenge in AI training is the difficulty in acquiring sufficient data. The Ludwieg Tube at Konkuk University provides a steady flow duration of approximately 100ms, and under the conditions of 10000fps using a high-speed camera, each experiment yields approximately 800 to 1000 images. Data augmentation techniques, such as adjusting the brightness, were applied to increase the dataset to @ images for training.

The surface pressure data was obtained using a pressure scanner, and ten repeated experiments were conducted under same conditions. From the results of repeated experiments, it was observed that pressure values within a consistent range were recorded at each pressure measurement point. Utilizing this information, data augmentation was performed within this range.

3.1. AI training for Shock waves Prediction

The artificial neural network utilized for shock waves training is U-Net. U-Net is a convolutional neural network widely employed in image segmentation tasks due to its ability to capture detailed spatial information. In predicting shock waves, the AI model takes an image without shock waves as input and generates an image with shock waves as output.

3.2. AI Learning for Plate Surface Pressure Prediction

The artificial neural network utilized for surface pressure training is LeNet. LeNet is a convolutional neural network, originally designed for handwritten digit recognition, known for its efficiency in image classification tasks. In predicting surface pressures on the flat plate, the AI model takes an image with shock waves as input and predicts the surface pressures on the plate as output.

4. Results of AI learning

The procedure for validating the aerodynamic data predicted by the AI models was carried out in two steps. Firstly, confirmed whether the trained AI models could accurately predict the aerodynamic data when provided with the learned data as input. Subsequently, Verified the predicted aerodynamic data when the AI models were provided with unseen, untrained data.

Both the shock waves prediction AI model and the flat plate pressure prediction AI model receive images as input. To preform predictions for unseen data, images not included in the AI training process were generated and fed into the models for prediction. This process aimed to confirm the generalizability of the AI models by evaluating their ability to predict aerodynamic data for shapes not encountered during training.

4.1. Prediction Results for Shock waves

The shock waves prediction model takes images without shock waves as input and generates images with shock waves as output. Initially, the shadowgraph images from wind tunnel tests that were part of the training dataset was used to predict shock waves. Fig. 4 shows the predicted results that the flow shape, including the oblique shock wave, interaction region, and reflection shock waves, generated by AI model closely resemble the actual wind tunnel test results.

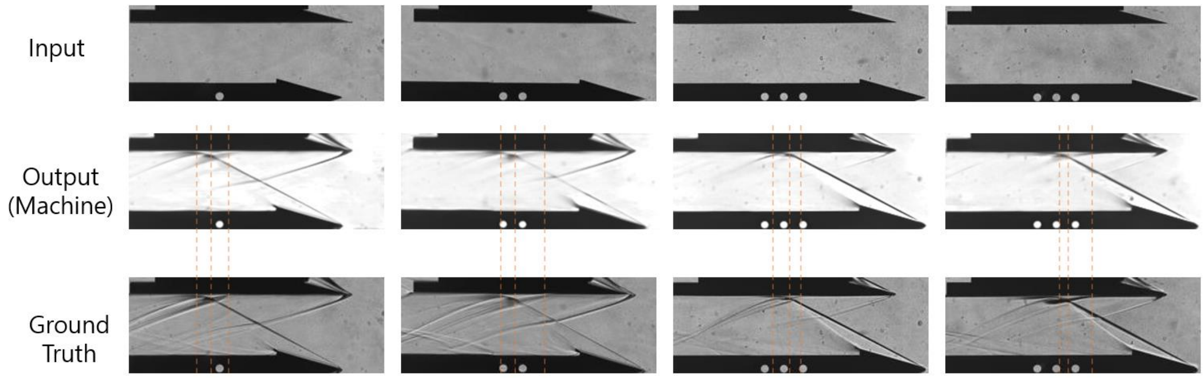

Fig 4. Shock waves predictions using training data as input

Next, images were generated in PPT(PowerPoint) with the same configuration as the wind tunnel test model to validate if the AI model could predict shock waves matching the results of the wind tunnel tests. Fig. 5 shows the predicted results that the structure of the shock waves predicted by AI model using images generated in PPT as input closely resembles the experimental data.

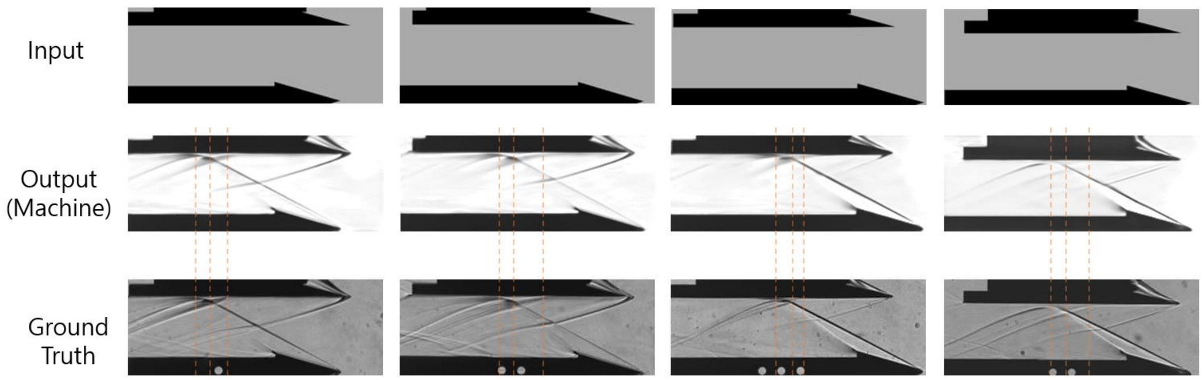

Fig 5. Shock waves predictions using a PPT-generated image with a known shape as input

Subsequently, images were generated in PPT for configurations not included in the AI training process, and the predicted shock waves were compared with CFD results for the same configurations. Fig. 6 shows the prediction results for configurations not used in the training process. These data were verified by conducting CFD calculations, as there were no ground truth data for these cases.

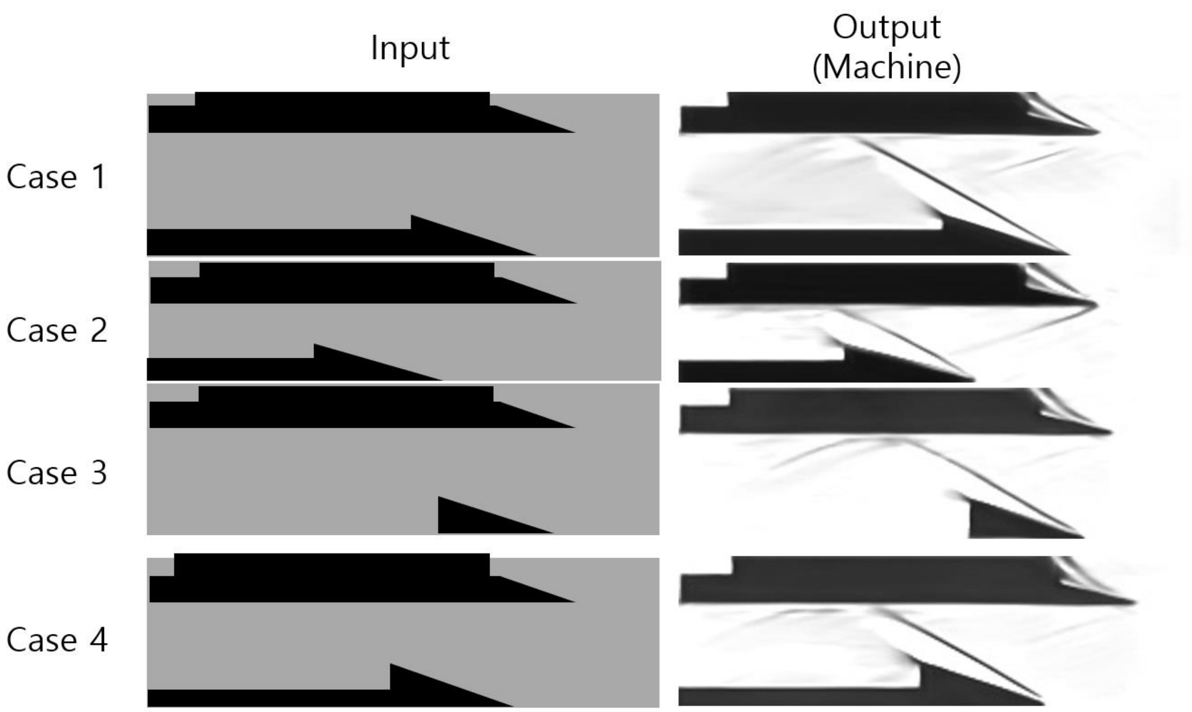

Fig 6. Shock waves predictions using a PPT-generated image with a unknown shape as input

4.2. Prediction Results for Surface Pressure

The prediction of flat plate surface pressure was conducted in two steps. Initially, the shock waves prediction AI model was used to predict shock waves images, and these predicted images were subsequently used as input to predict the surface pressure on the flat plate.

First, images were generated in PPT as the shape of wind tunnel models. The shock waves prediction AI model then predicted the shock waves. Fig. 7 shows the surface pressure predictions using the predicted shock waves images as input. The predicted surface pressure on the flat plate matches the wind tunnel test data.

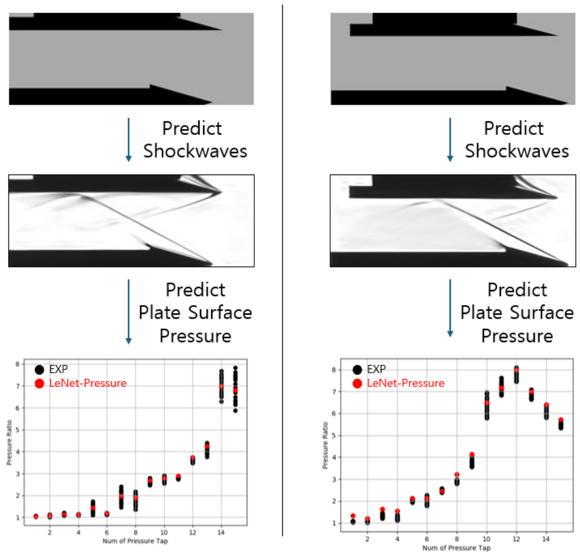

Fig7. Predicting shock waves and surface pressure using a PPT-generated image with a known shape as input

Next, surface pressure predictions on the flat plate were carried out for configurations that were not part of the training dataset, utilizing the predicted shock waves images as input. CFD simulations were performed and the predicted surface pressure values on the flat plate were compared. Fig. 8 to Fig. 11 shows the flow field structure and flat plate surface pressure results of CFD calculations and AI prediction results.

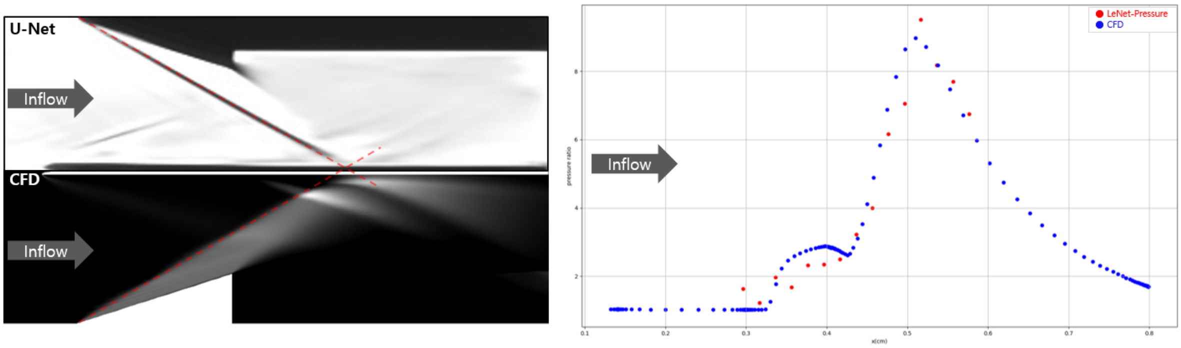

Fig 8. Predicting shock waves and surface pressure using a PPT-generated image with an unknown shape as input: case 1

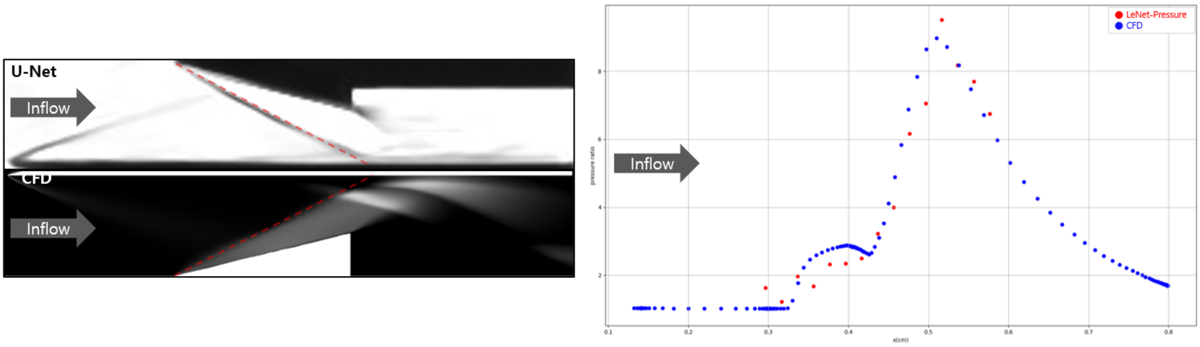

Fig 9. Predicting shock waves and surface pressure using a PPT-generated image with an unknown shape as input: case 2

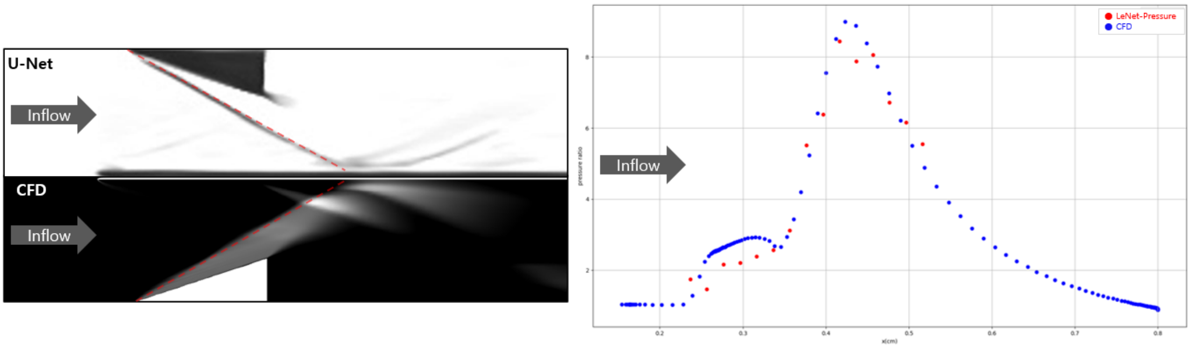

Fig 10. Predicting shock waves and surface pressure using a PPT-generated image with an unknown shape as input: case 3

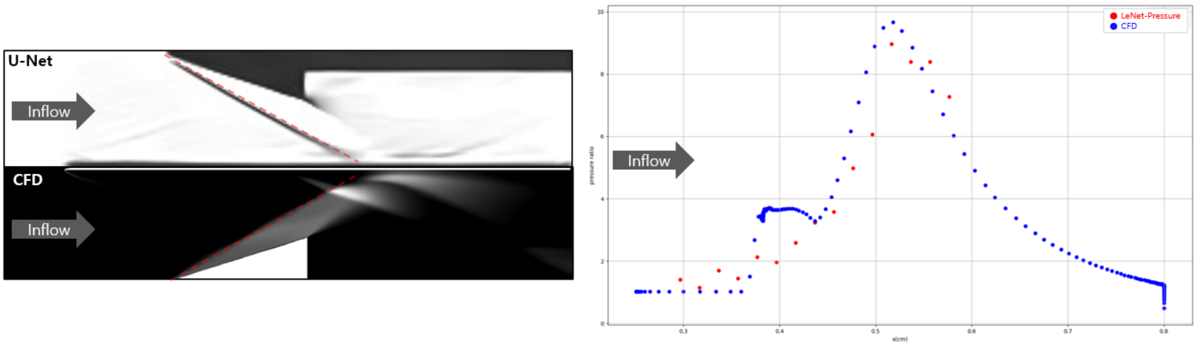

Fig 11. Predicting shock waves and surface pressure using a PPT-generated image with an unknown shape as input: case 4

As shown in Fig. 8 to Fig. 11, the locations where the oblique shock wave interferes with the flat plate boundary layer are consistent, and the predicted surface pressure on the flat plate demonstrate a reasonable agreement between the AI predictions and the CFD simulation values.

5. Conclusion

In this study, an alternative method for acquiring aerodynamic force data using AI, distinct from the conventional approaches of wind tunnel testing or CFD simulations was proposed. The wind tunnel experiments were conducted using a shock wave-boundary layer interaction model, and shadowgraph images and flat plate surface pressure data were using for AI training. Two AI models were employed for two different training. The first model received images before shock waves generation as input and predicted images with generated shock waves as output. The second model, taking images after shock waves generation as input, predicted the surface pressure on the model.

Validation of the predicted data involved generating images with the same shapes to those used in the training dataset, as well as images with configurations not encountered during training, using the PPT. The verification results confirmed the validity of the AI predictions when compared with CFD data.

However, it is challenging to assert that the proposed technique completely replaces conventional methods for acquiring aerodynamic data in terms of accuracy. Nonetheless, it is believed that this approach could result in significant cost savings, especially in the early stages of research for preliminary design or when determining the research direction.

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