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High Performance Deep Learning Framework for Computational Fluid Dynamics Modelling in Aerospace Applications

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Abstract

High fidelity modelling and simulation of complex fluid dynamic phenomena has become a crucial tool for advancing aerospace technology. For many years, a key technique that is utilized to analyze aerodynamic behavior, predict flow behavior, and improve aircraft design, is termed as Numerical Fluid Flow Analysis. For the purpose of improving the modelling of Computational Fluid Dynamics (CFDs) in aerospace engineering, a high-performance Deep Learning (DL) framework that integrates Numerical Fluid Flow Analysis simulations and data-driven neural architectures is presented in this study. This study speeds up aerodynamic analysis, cut down computational costs, and maintain physical accuracy, this will support in attaining optimized airplane structure, main goal of this study. Standard CFD solvers with sophisticated DL-based approaches, like Numerical Fluid Flow Analysis, Physics-Informed AI Network, fusion framework that consider statistical constraints and physical constraints are all integrated in the suggested method. A precise prediction regarding critical aerodynamic characteristics like lifting and dragging, pressure distribution, and turbulent kinetic energy over various air foil configurations (NACA 2412, 4415, and 0012) is offered by this framework based on high-fidelity CFD datasets and experimental wind tunnel data. From the flow fields, spatial-temporal features are extracted automatically with the DL frameworks. Identifying nonlinear interactions within boundary layers and turbulent zones are mostly computationally expensive when resolved using conventional numerical solvers. But the DL model has the potential to detect nonlinear interactions within boundary layers and turbulent zones. An average fidelity of 97.2%, accuracy of 98.2%, and F1-score of 97.8% are attained by the suggested model, and it executes better than the baseline architectures like ResNet, MoCo, and Transformer networks, as demonstrated by the comparative analysis. From this analysis, it is validated that the suggested model attains high predictive performance. Robustness and generalization are improved by integrating PINN, as it ensures compliance with governing physical laws (e.g., Navier-Stokes equations). This hybrid model helps in reducing the simulation time up to 60% without impacting fidelity, so this model is considered as an effective tool for real-time aerodynamic design, flight optimization, and future intelligent aerospace systems.

Keywords: Airplane structure, Aerospace analysis, Deep learning, And numerical fluid mechanism.

1 | Introduction

Fluid mechanics is a basic topic of study that examines the flow of motion of fluids and properties. This it offers foundational principles, and has broad applications over many scientific and technological applications including biology [1], environmental science [2], aerodynamics [3], and chemical engineering [4]. Now, researchers and engineers are increasingly using an effective tool named Computational Fluid Dynamics

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(CFD). This CFD simulates fluid motion. It supports engineers and researchers to analyze complex fluid phenomena in aerospace, automotive, energy, and healthcare industries. Here, the basis of the conventional CFD models is numerical solution of Partial Differential Equations (PDEs). This PDE enable the CFD model to understand and predict fluid behavior [5]. Here, capturing multi scale phenomena, high computational costs, and modelling complex turbulent flows are some of the difficulties that CFD experiences, despite its benefits [6]. For several key reasons like accuracy, scalability, and efficiency, an effective simulation method must be needed because there is high complexity of fluid dynamics problem. The study of the mechanical behaviors of elastic objects in airflow is known as aeroelasticity. These problems include the coordination between aerodynamic pressures and elasticity objects as well as the mechanical properties of elastic objects in fluids. The aerodynamic performance of aircraft is greatly impacted by the problem of aeroelasticity, which causes structural damage to aircraft [7].

The theory of aeroelasticity, as a result of coupling effects of aero mechanism, elastic, inertial, and thermal forces [8], has been extensively studied and numerous theoretical achievements have been formed. In the early development, the main objective of aeroelasticity was to avoid the occurrence. The traditional method of increasing the weight of the structure restricted the improvement of the aircraft's speed. Chemical emissions are the main issue that may restrict modern air transportation in attaining long term sustainability. These chemical emissions become worse with an annual increase in air travel of over 5%. Advancing airplane structure is one effective method for reducing these emissions, it also facilitates in enhancing transport efficiency, and reducing fuel consumption. Enhancing the aircraft's lift generation capacity to maximize payload and minimizing drag to lower propulsion requirements during cruise are two ways to do this. Practically, the objective is to maximize the L/D ratio for improving aerodynamic efficiency [9]. Researchers and engineers have looked into a variety of technological approaches to accomplish this, ranging from more sophisticated and creative solutions, like novel aircraft configurations and alternative propulsion system frameworks, to more straightforward and conservative techniques, like passive flow control with flow modifying vanes. The development of an effective maneuverable aircraft is made possible by aeroelastic effects research. For the optimization of airplane structure, accurately capturing the nonlinear aerodynamic changes related to aeroelasticity is crucial. Wind tunnel experiments, and numerical simulations are the 2 main techniques that are used in evaluating the aeroelastic characteristics of new aircraft configurations [10]. Then, it utilizes finite element analysis on digital computers, and this method is especially useful for solving aeroelastic problems.

For instance, Stickan et al. [11] used experimental methods to investigate the Limit Cycle Oscillation (LCO) behaviors of transport aircraft wings at transonic speeds. Ghiringhelli et al. [12] employed a three-dimensional wing model to experimentally test a method for designing active control flutter suppression systems. Additionally, Thomas et al. [13] utilized CFD to investigate how nonlinear aerodynamics impact the divergence, flutter, and LCO behaviors of a transonic airfoil configuration [14] through numerical simulations. Given the complexity and cost of physical testing, conducting extensive experimental studies on aeroelasticity is not practical, making CFD based simulations a more efficient and effective approach for early stage aeroelastic research. The current study objective is to assess the feasibility of assessing flow control factors employed in airfoils using advanced machine learning methods.

For this objective, both pressure and velocity fields around distinct Gurney closures and spinning tiny tabs were constructed on the airfoil by means of a CNN are predicted. Section 2 Reviews the current state of research, including various methods and studies that combine machine learning with CFD, such as turbulence modelling, aeroelasticity, and optimization of aircraft designs using Deep Learning (DL). Section 3 Details the CFD setup utilized by this paper, including the RANS mathematical expression, turbulence models, and the computational domain used for simulations. The fluid dynamics problems are resolved in this section by using many air foils and computational methods. The integration of CFD with DL is briefly explained in Section 4. Data pre-processing, data collection, and feature extraction are all included in this section. For the purpose of improving CFD procedures, ML Models Like Multilayer Perceptron's (MLPs), CNNs, and PINNs are implemented. Results of the simulation are discussed in Section 5, and it helps in analyzing the efficiency

of predicted methods. This section compares the performance of the new methodology with traditional machine learning models like ResNet, MoCo, and Transformer, and discusses its effectiveness in predicting aerodynamic behaviors and finally, Summarizes the research findings, enhancing the effectiveness of combining DL with CFD to improve prediction accuracy and reduce computational costs in aerospace design. The study emphasizes the potential for this integrated approach to transform aerospace engineering by enhancing simulation efficiency and supporting design optimization.

2| Literature Review

Beck and Kurz [15] presented a review of research state in data-oriented instability conclusion modelling. They offered perspectives on the difficulties and open problems, as well as on the benefits and guarantees ML applying techniques to model identification, parameter estimation and closure term renovation, primarily from the viewpoint of big Eddy modelling and correlated models. They emphasized that constancy among the model, training data, the underlying physics and the divergence was a primary factor for an effective ML-augmented modelling approach. To make the interaction accessible to general users, the authors introduced both the turbulence modelling problem and the main ML framework and methods in a self-consistent, concise way.

Their study provided a survey of current data-driven model concepts, highlighted significant developments, and placed them in the relevance for the proposed problems. Wang and Ma [16] investigated the relevance of DL methods-particularly DNN, Long Short-Term Memory (LSTM) and LSTM-Neural Networks (LSTM-NN) to forecast panel flutter in aerospace structures. Their aim was to enhance the precision and effectiveness of estimating aeroelastic characteristics under varying flight circumstances. Using a hypersonic smooth surface serves as the test configuration, they incorporated multiple flight circumstances into the aero elastic formulation and generated architectural vibration information to build an extensive training record. The inputs are divided into validation, training and testing sets, including data's characteristics like Mach number, panel aspect ratio, air density and decay rate.

The authors stressed the significance of identifying the right hidden layers, epochs, and neurons to minimize over fitting. While DNN, LSTM, and LSTM-NN all benefited from increased neurons and layers up to a certain point, excessive model complexity reduced accuracy and induced overfitting. In terms of performance, the LSTM-NN attained the greatest efficiency in categorization tests by properly gathering consecutive characteristics whereas LSTM is effective in forecasting flutter Mach values due to its ability to simulate persistent dependencies and irregular interactions. In spite of LSTM's higher precision, it requisite more training period because of computational complication, demanding a trade-off among effectiveness and efficiency.

Overall, their result demonstrated that DL-particularly LSTM-NN was highly efficient for sectional flutter forecast, highlighting its ability for more aerospace technology features. Negoita and Hoth [17] Azie introduced a new way to test how well an airfoil work by developing and teaching an advanced AI-powered neural approach to predict utilizing information from a CFD solver to determine hydrodynamic characteristics and increased stress remuneration. They first developed a mechanized CFD solution to generate the massive database required for efficient ANN teaching. The mechanization procedure involved interface and topology generation in addition to incorporating the publicly accessible SU2 model for computations of aerodynamics, selected for its flexibility and ease of assimilation. Several aerodynamic studies were conducted, and after gathering an extensive information set, the values were standardized, and multiple ANN configurations were trained by varying architectures, hyperparameters, and layer settings. Following extensive evaluation and verification, the most effective architecture was shown to have the best generalization abilities, with the least mistake rates and most precise forecasts on both training and unknown data. Their ML-driven method, proposed an alternative to conventional CFD models, demonstrated incredible robustness and precision, effectively captivating intricate aerodynamic characteristics while extensively decreasing the CFD modeling operational expenses. Multi objective genetic approach of UAV

patterns is suggested by Karali et al. [18]. This method integrates DNN with a multi-objective genetic approach, and it may support in resolving issues in conventional methods. This approach makes it possible to evaluate multiple design options and effectiveness metrics for diverse operational requirements in an efficient manner [1]. When compared it to conventional methods, it achieves a significant reduction in computing time by 3 orders of magnitude. This paper provides evidence of the model's flexibility in optimizing UAV designs for many mission scenarios Like Surveillance, Reconnaissance (ISR), intelligence, Suppression of Enemy Air Defenses (SEAD) and Combat Air Patrol (CAP). By using this technique, various design needs including structural weight, aerodynamic efficiency, and stealth are all optimally balanced. One important aspect of this strategy is its flexibility in responding to certain operational needs. Fast prototyping, simulation of creativity is facilitated by the integration of AI in prior-stage aerospace methodologies.

So, this integration may deliver novel advancements, and it was demonstrated by the outcomes. For revolutionizing UAV design, AI driven optimization is considered as an effective and dependable method. Hasan et al. [19] suggested a quick and dependable analysis technique that combines neural network learning with numerical fluid dynamics for the aerodynamic structure of high-speed aircraft wings. The benchmark aircraft for NASA's Common Research Model (CRM) utilized their architecture and relied on automated CFD simulations evaluating 160 CRM wing planform variations from an aerodynamic standpoint. Two algorithms-eXtreme Gradient Boosting (XGB) and Light Gradient Boosting Machine (LGBM) were investigated when training ML surrogate models using the generated information. After training with 80% of the dataset and testing ML analogs were used to investigate a wider range of designs for the rest 20%. with optimal configurations identified through a MOGAO Algorithm. Each ML-based vision platform was further validated through CFD simulations, and the results were compared with those obtained from conventional CFD-based optimization. The comparison proved highly favorable, as the best ML-based vision platform achieved comparable performance to its CFD maximized equivalent, including a 14% superior lift-drag ratio, while reducing computational cost by half. Overall, their study demonstrated the effectiveness of ML-driven methods for wing optimization and highlighted the potential of data-driven paradigms to transform aircraft design. Zan et al. [20] developed a ML based on a CNN to specify aerodynamic modelling and optimization problems. The CNN was employed to implicitly withdraw characteristics from input while significantly reducing the number of trainable parameters through parameter sharing and local connectivity that proved advantageous for addressing multilayered issue with prohibitive training costs. An ultrafast wing, equivalent to the Sanger aviation plane carrier wing, was used as the experiment case. The wing was characterized via the free-form deformation approach, and 109 factors such as flight status and aerodynamic shape parameters were identified as the model's parameters.

In order to create an aerodynamic record, over 7000 test case produced by the Latin hypercube testing approach were assessed using CFD models with a Reynolds averaged Navier Stokes model. to build an aerodynamic database. A CFD method was then trained on this dataset and subsequently applied to aerodynamic shape optimization. Their results demonstrated the CNN's the capacity to quickly optimize over a variety of flight conditions while maintaining high reliability and accuracy. Basem et al. [19], employed using a predictive surrogate approach that combines the Proper Orthogonal Decomposition (POD) methodology with the LSTM network, flow variables are estimated while the temporary coolant injection stage from the nose cone [21]. Using this hybrid method, they evaluated the counterflow jet's pressure, velocity and mass fraction and explained the sources of discrepancy between the surrogate model and the full-order model. POD modes were defined to enable efficient prediction of various variable flows. The efficiency of the POD was assessed across different training and test ranges, and the results showed that its performance was appropriate when 80% of the obtainable information was used for instructing. However, the intricacy of the vortices in the loop zone was discovered to be the reason for the larger prediction mistakes of the coolant mass percentage and axial velocities Silvestrini and Lavagna [22] introduced the most relevant characteristics of artificial neural network approaches for navigation, spacecraft dynamics control and guidance. They examined the general NN-framework and training methods, highlighting the pros and cons of utilizing certain issues.

In specific, they reviewed the applications of artificial neural structure for identifying system, optical navigation, control synthesis and comparing them through both qualitative and quantitative metrics. Their review also included innovative methods, which combined neural methodologies with conventional methods to improve efficiency, as well as end-to-end DL algorithms for spaceship guidance, control and navigation. Shafi et al. [23] proposed a real-time DL-driven framework for locating defective parts in the aerospace industry at various phases of production. They employed a CNN to identify and categorize intermediately aberrant conditions in an individual production procedure. Since post-integration analysis of aircraft components is laborious and consumes time, often leading to costly risks, their AI-based system aimed to execute examination and identification of flaws during earlier phases to minimize the need for re-production following assembling.

Furthermore, the framework analyzed the significance factor such as rework expenses and delays through current data and a probabilistic control method. Defects were detected and classified with CNNs and a teachable machine prior to assembly, demonstrating the system's ability to reduce operational risks. The results indicated significant benefits, with statistical findings a 34.32% decrease in overall expenses and a 52.88% decrease in time interruptions. Air tests of the finished aircraft were performed after ground tests to determine the significance value, confirming the framework's ability to enhance cost control and minimize delays caused by rework. Wang et al. [22] proposed a technique for automatically detecting defects by combining machine vision and radiography inspection with computer vision for aeroengine turbine blades. They introduced an approach for detecting errors named DBFF-YOLOv4, which employed structured fault characteristics are extracted using two root structures from X-ray images. All characteristic maps were combined into a new fusion form that playing a critical role in the detection framework. In addition, they established an approach for identifying and detecting defects capable of processing entire X-ray pictures of turbine wings X-ray images. To enhance training, 9 crop phases for each fault, along with changes in brightness and flipping, were used for data augmentation. Their results demonstrated that the system score cut-off of 0.5 with a 91.87% recall percent, 96.7% accuracy rate, and 7% error rate. The findings confirmed that repeated removing and extending significantly improved detection accuracy, providing a new approach for automatic radiographic testing of turbine blades.

3 | Computational Approach and Set-up

In this paper, the RANS equations are utilized by restricted volume to solve formulation, where regional separation is used with a 2nd level accurate upward scheme, and temporal advancement is performed through a first order implicit pseudo-time stepping approach. To address the high computational demands associated with the very large Reynolds numbers characteristic of aerospace flows, wall functions are employed to model near wall effects rather than fully resolve them. Specifically, the enhanced wall function approach is adopted, which significantly relaxes grid resolution requirements near solid boundaries while adequately capturing the drag contributions induced by boundary layer shear stresses.

In high Reynolds ratio regimens, this method is very effective, here dynamic impacts are significantly larger than viscous contributions. For turbulence closure, realizable k- ϵ model is used. This model is effective and executes better than standard methods for dealing flows with large pressure gradients, separation, and recirculation. When aerospace configurations having complex boundary layer behavior, this model is effective. The working fluid is characterized as an ideal gas, Sutherland's law is used to determine viscosity, and thermal properties with constant specific heat fixed at 1006.43 J/kg·K and constant conductivity at 0.0242 W/m·K. For high performance modelling of complex aerodynamic phenomena in aerospace engineering, physical fidelity and numerical efficiency must be effectively balanced, and it was ensured in this computational setup. Simulations are demonstrated as *Fig. 1*, over the NACA 2412, NACA 4415, NACA 0012 belong to a class of air foils that have a pressure recovery region along their upper surface that creates an effortless shift from laminar to turbulent flow a phenomenon known as a "transition-ramp". These air foils are used by wind turbines. Simulations were executed by using Structured C-meshes measuring 394x124

in both the wrap around and normal directions. A low Mach number of 0.2 is chosen to be realistic of wind turbine settings, and simulations are run at Reynolds ratios of 0.5, 1, 2, and 3×10^6 , accordingly.

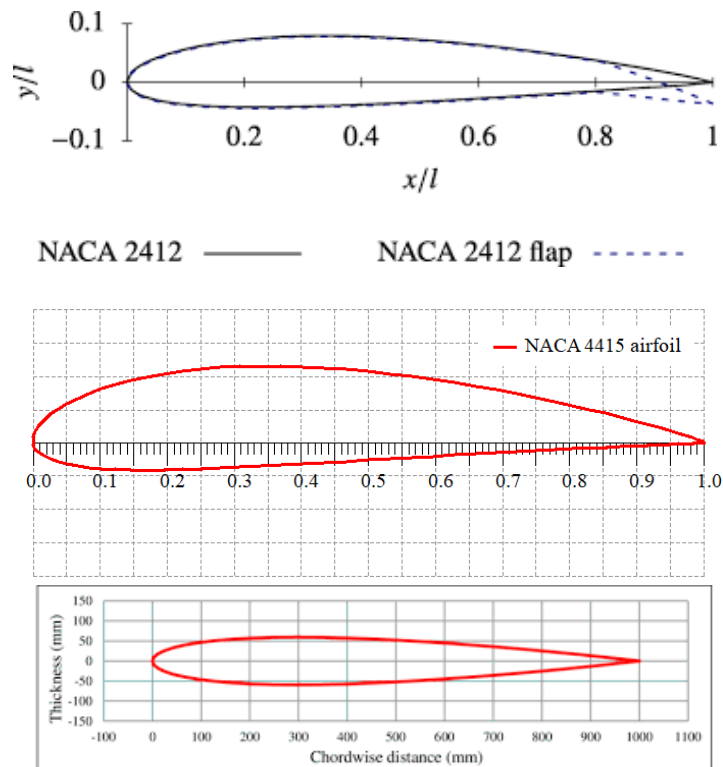


Fig. 1. Simulations over the NACA 2412, NACA 4415, NACA 0012.

Balance among physical fidelity and numerical efficiency is ensured by this computational setup. High performance modelling of complex aerodynamic phenomena related to aerospace engineering is also made possible by this computational setup. A constant numerical configuration was utilized for executing computational simulations, and modifications have been made to adapt to specific flight conditions. The aircraft was partially modelled, and utilizing inherent coherence greatly reduces computational expenses and maintaining physical accuracy. In order to minimize inaccurate interactions, the computational domain spanned roughly $64 \times 15 \times 16$ half-span lengths in the vertical, lateral, and axial axes, respectively. Boundary conditions as slip less condition on the aircraft surface, and stream free under constant circumstances prescribed at the distant area boundaries through a distant area impact (or feature) formulation were applied. The described boundary conditions are fully consistent with standard practices in prior aerospace CFD studies. From the CAD airplane structure, the disordered pattern was generated, and it is used to divide the zone. For high performance aerodynamic simulations, these disordered patterns offer adaptability in identifying geometric complexity, and preserving numerical robustness.

4 | Proposed Methodology

In order to integrate DL into CFD, traditional simulation techniques must be combined with data-driven approaches. The workflow of applying ML in CFD includes input acquisition and pre-processing to developing and validating ML models, application to improve CFD workflows. The ML makes large scale simulations easier to handle, and the way the ML reduce dimensionality of CFD problems without impacting accuracy, are all demonstrated in this study. When combined with ML, sparse modelling techniques provide a computationally efficient way to handle complex fluid behaviors.

4.1 | Data Acquisition and Preprocessing

For training robust DL models, both simulation based and experimental data are needed for High performance computational modelling. Under a variety of aerospace flow conditions, the dataset is assured to accurately depict fluid dynamic behaviors in this step. High performance computational modelling and the integration of DL for complex aerospace fluid dynamics are based on data acquisition.

High fidelity CFD datasets are utilized in this study. It includes Reynolds-Averaged Navier-Stokes (RANS) and Large Eddy Simulation (LES), and Direct Numerical Simulation (DNS) solutions for a variety of benchmark aerodynamic cases like air foils, finite wings, jet plumes, and cavity flows, and it is used as a main source of data in this study. Comprehensive flow fields like velocity components (u , v , w), pressure distributions (p), and temperature variations (T) are offered by these datasets. For identifying complex physical phenomena that control aerospace flows, these comprehensive flow fields are crucial.

From wind tunnel simulations, experimental data like Particle Image Velocimetry (PIV) and distributed pressure sensors are utilized for CFD simulations. It facilitates validation and bridge the gap among numerical predictions and real-life findings. Then, accuracy and computational efficiency are effectively balanced by implementing hybrid multi fidelity approach. Large volumes of low resolution CFD data are utilized by this hybrid multi fidelity approach for broad mapping design spaces. On the other hand, the low-resolution data is then supplemented with smaller, carefully chosen sets of high fidelity CFD data, and it enhances DL model training. Two complementary sources are merged to form datasets for ensuring breadth and depth, and facilitating effective optimization in aerospace engineering applications, robust surrogate modelling, and accurate prediction of complicated flow features.

4.2 | Feature Extraction

A crucial phase named feature extraction is executed after the data is cleaned. This feature extraction method prepares the data for ML algorithms to use. The CFD generated datasets and DL models are effectively connected by the feature extraction method. For effective training, the most physically relevant and information rich features are captured, and it was ensured by this feature extraction. A wide range of flow field descriptors are covered by the extracted features in this analysis. Here, velocity components (u , v , w), static and dynamic pressure, vorticity magnitude (ω), turbulent kinetic energy (k), temperature gradients, and Reynolds stress tensors are some of the extensive ranges of flow field descriptors. Crucial physical measures that control aerodynamic behavior like lift, drag, and stall onset are reflected in features and it is observed, so these features are selected.

Here, a multi-level feature hierarchy is introduced for an effective learning. The convolutional filters detect spatial patterns in velocity and pressure fields, and it is utilized by the network thus records local flow structures such as boundary layer separation, laminar to turbulent transition, and wake formation at low level. The kernel-based operations and spatial pooling operations are the components that are utilized for detecting intermediate features like shear stress and recirculation zones in the mid-level. The model can comprehend the connection between aerodynamic forces and surface geometry via this methodology. By utilizing fully connected layers, attention layers, and integration of spatial and temporal correlations, high level predictions of global aerodynamic responses like lift-to-drag (L/D) ratios, flow divergence, and shock boundary layer are generated.

Here, two powerful methods like Z-score normalization and min-max scaling are used to rescale features. This application may help in improving the data consistency and model's efficiency. To reduce unnecessary CFD data and to preserve main physical features, Autoencoders are effective. Then, PCA effectively simplifies complexities. By implementing both Fourier feature maps and wavelet feature maps, complex and recurring flow features like oscillatory disturbance phases and vortex erosion are captured. Multi-resolution, physics-aware feature extraction process are utilized by the DL model to achieve 2 key objectives like minimized computational overhead, and improved predictive precision in complex aerospace flow environments. One

important technique that allows both CNNs and PINNs to effectively reconstruct aerodynamic characteristics is the utilization of a generated feature vector as a compact representation.

4.3 | Deep Learning Methods for Computational Fluid Dynamic

RNNs and CNN are DL techniques that are widely utilized when dealing with high-dimensional aerospace datasets. RNN and CNN models work well in situations when it's critical to capture intricate, nonlinear relationships between flow parameters like turbulence prediction and aerodynamic flow analysis.

Well known scientific rules like Navier-Stokes equations are integrated directly in the PINN model, and it supports in ensuring physically consistent NN predictions. In aerospace fluid dynamics, unsupervised methods like clustering and Autoencoders are utilized for accomplishing the following tasks like anomaly detection, flow pattern recognition, and data driven model reduction.

Integration of NN in conventional engineering and scientific computing revolutionizes aerospace research and applications. Problems when dealing significant computational burden of simulating nonlinear, multi scale aerodynamic phenomena are effectively resolved by this integration in CFD. The robust function approximation and pattern recognition abilities of the NN facilitates in minimizing dependence on conventional solvers, and also assist in improving prediction accuracy for complex aerospace flows. Turbulence modelling, aerodynamic flow field reconstruction, surrogate based design optimization, and real-time flight prediction are just a few of the applications.

Main pillars of this intelligent driven CFD model in aerospace systems are broader design space exploration, uncertainty quantification, reduced computational overhead, and adaptive control strategies. In order to fulfil the increasing demand for effective, dependable, and high-fidelity aerodynamic analysis, the incorporation of neural networks into CFD represents a paradigm shift in aerospace engineering by combining physics-based solutions with data driven intelligence.

4.3.1 | Multilayer perceptrons

MLPs, also known as FCNN, used widely by advanced machine learning complex algorithms. It has been mathematically established that, with sufficient depth, a MLPs can approximate any continuous function, providing a theoretical basis for their broad applicability.

An MLP is structured in multiple layers of interconnected artificial neurons, as illustrated in *Fig. 2* a four-layer MLP. This MLP is a quad-stage concept. The input layer does not perform computation. Each neuron in a given region is connected to each neuron in the subsequent layer through associated weights and biases. Typically, an MLP is composed of an input layer, an output layer and one or more hidden layers, and an output layer. The input layer gets the unprocessed inputs, hidden layer transform and extract features from this data, and the output layer produces the concluding results. The learning process of an MLP involves two main stages as forward propagation, where information passes over the network to create outcomes, and backward propagation, here errors are propagated backward to update weights and biases.

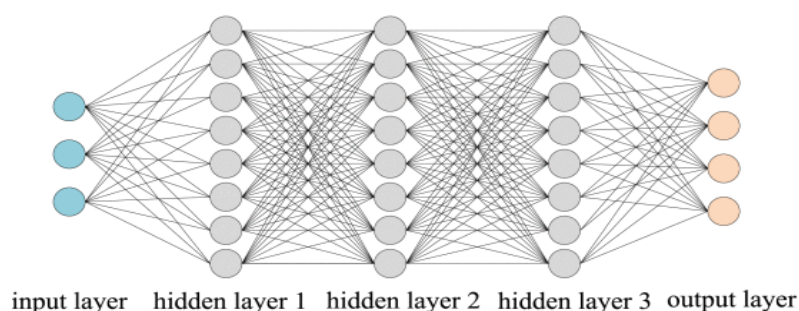


Fig. 2. Layers of MLP.

Forward propagation explains how generated information move sequentially from the input layer to the output layer in an MLP. As illustrated in *Fig. 3*, suppose the input layer has n neurons and the hidden layer contains m neurons. Let $w_{ij}^{(l)}$ represent the weight connecting the i^{th} neuron in layer $l - 1$ to the j^{th} neuron in layer l , and $b_j^{(l)}$ be the bias term of the j^{th} neuron in layer l . The forward propagation for a given input sample z can be defined as in *Eq. (1)*, where $f(\cdot)$ is the activation function applied at layer l .

$$a_j^{(l)} = f\left(\sum_{i=1}^n w_{ij}^{(l)} a_i^{(l-1)} + b_j^{(l)}\right). \quad (1)$$

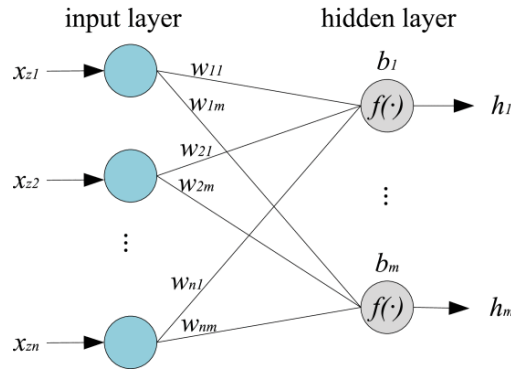


Fig. 3. Forward propagation.

4.3.2 | Convolutional neural network

In this context, CNN is considered as dominant feature extractors. For feature extraction, its workflow contains encoding-CNN-decoding pipeline. To track ocean eddies, CNN-LSTM framework was suggested by Franz et al. [24] Incorporating both vector values (like velocity) and scalar variables (like pressure) into the CNN inputs significantly increases the accuracy of extracting shock features in airflow studies, and it was demonstrated by Liu et al. [25] Interactive real-time post-processing frameworks have been presented to further improve analysis efficiency. These frameworks use DL to deliver quick feedback and intuitive target region selection. For example, Han et al. [26] applied clustering techniques to streamline and flow surface data before feeding the clustered results into a 3D-CNN, thereby enabling rapid classification and visualization. Such decoded outputs facilitate user driven exploration by allowing quick selection of projection planes and immediate feedback, ultimately improving the responsiveness and practicality of flow feature analysis in aerospace applications. A traditional CNN structure is depicted in *Fig. 4*.

Convolutional layer, pooling layer, and fully connected layers are among the various layers that make up the network. A traditional CNN for predicting complex steady aerodynamic responses. Two convolutional layers, two pooling layers, and two fully connected layers make up the network. The CNN can identify the associated aerodynamic reactions, including the input wing's Lift (L) and Drag (D).

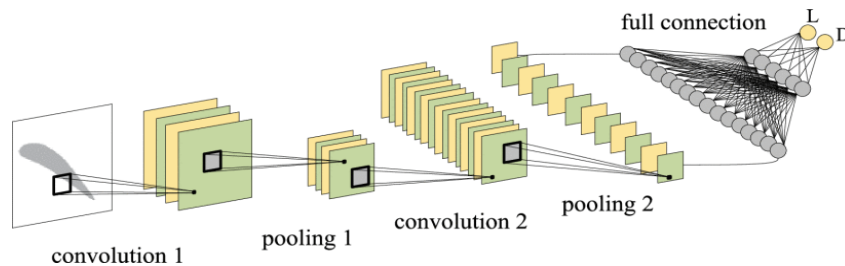


Fig. 4. CNN structure.

4.3.3 | Physics-informed neural network

The Neural network architecture of the PINN demonstrated as Fig. 5, is a transformative tool in aerospace engineering, providing a bridge between traditional physics-based solvers and modern DL. Unlike conventional NN that rely exclusively on physics-informed NN, data, incorporate the fundamental principles of fluid dynamics and structural mechanics directly into their training process.

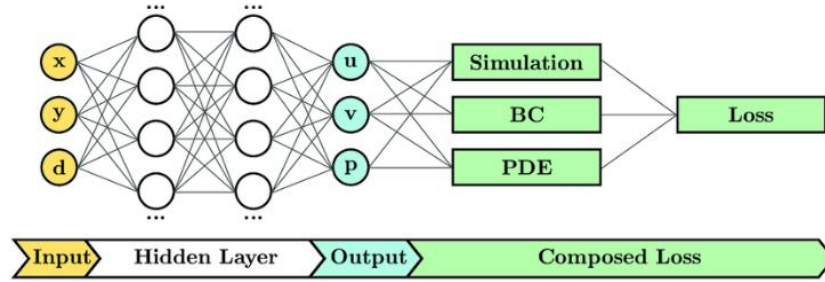


Fig. 5. Neural network architecture of the PINN.

The general idea is that the neural network outputs approximate physical variables such as pressure $p(x, t)$ and velocity $u(x, t)$ and, while both physics restrictions and information reliability are enforced by the reduction rate. For example, in the case of incompressible aerodynamic flows, the Navier-Stokes equations are incorporated into the network as soft penalties as Eqs. (2) and (3):

$$\nabla \cdot \mathbf{u} = 0, \quad (2)$$

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla) \mathbf{u} = -\nabla p + \nu \nabla^2 \mathbf{u} + \mathbf{f}, \quad (3)$$

Here, Eq. (4) enforces mass conservation, while Eq. (5) ensures momentum balance with viscosity ν and external forces $\mathbf{f}$. The neural network approximations $\hat{\mathbf{u}}$, $\hat{p}$ are substituted into these PDEs, and their residuals are minimized during training. Thus, the PINN reduction rate becomes a balanced combination of components driven by data and physics as Eq. (4):

$$\mathcal{L} = \mathcal{L}_{\text{data}}(\hat{\mathbf{u}}, \hat{p}) + \lambda_1 \|\nabla \cdot \hat{\mathbf{u}}\|^2 + \lambda_2 \left\| \frac{\partial \hat{\mathbf{u}}}{\partial t} + (\hat{\mathbf{u}} \cdot \nabla) \hat{\mathbf{u}} + \nabla \hat{p} - \nu \nabla^2 \hat{\mathbf{u}} - \mathbf{f} \right\|^2, \quad (4)$$

This formulation ensures that even with sparse experimental or CFD data, the solution remains physically meaningful. In aerospace studies, such an approach is valuable for applications ranging from turbulence modeling and shock boundary layer prediction in supersonic/hypersonic flows, to aeroelastic simulations where fluid equations (Navier-Stokes) are coupled with structural PDEs, such as the Euler-Bernoulli beam Eq. (5):

$$\rho s \frac{\partial^2 w}{\partial t^2} + EI \frac{\partial^4 w}{\partial x^4} = q(x, t), \quad (5)$$

5 | Results

Initially, we demonstrate how the network framework can precisely determine the stresses factor and velocities surrounding various airfoils based just on the form of the airfoil. Then, we objectively examine the defect measurement followed by a succession of findings which indicate accessibility, efficiency and reliability of the network.

5.1 | Efficiency Analysis

Comparative tests were carried out with a number of other popular supervised learning approaches in order to assess this method's fault classification capabilities as shown in Fig. 6 to 8 and Table 1-3. Transformer,

MoCo, and Residual Network (ResNet) are among the techniques that are compared. Eighty percent of the fault dataset was utilized for training set, while the excess information was employed for the evaluation set. The same development and evaluation process was applied to each model. The outcomes of the comparative tests are presented. This paper evaluates the suggested using evaluation metrics. Accuracy metric assesses the proposed model's expected quality. In relation to the dataset entire number of occurrences, this determines the percentage of accurately predicted occurrences, including True Negatives (TN) as well as True Positives (TP). The proportion of times the model generated an optimistic forecast is known as accuracy. The TP rate predictions among all positive cases are called as recall. The harmonic mean of memory and precision is represented by the F1 score. A model that continuously demonstrates high recall and precision levels has a better F1 score. In Eqs. (6)-(9), TP indicates TP, TN indicates TN, FP indicates false positives and FN indicates false negatives.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (6)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (7)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (8)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (9)$$

Table 1. Comparison results of performance indicators of NACA 2412.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet	94.3	94.9	94.8	96.3
MoCo	95.4	93.1	93.6	97.1
Transformer	93.2	94.3	93.5	94.2
Proposed	96.2	98.2	99.3	97.8

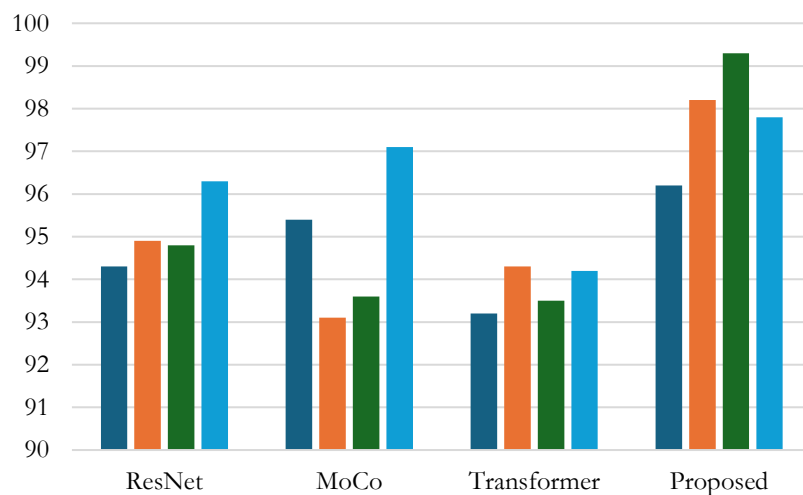


Fig. 6. Comparison results of performance indicators of NACA 2412.

Table 2. Comparison results of performance indicators of NACA 4415.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet	94.3	92.1	91.5	93.6
MoCo	95.2	91.2	96.4	92.1
Transformer	96.1	92.1	95.1	92.6
Proposed	97.2	95.2	98.5	96.3

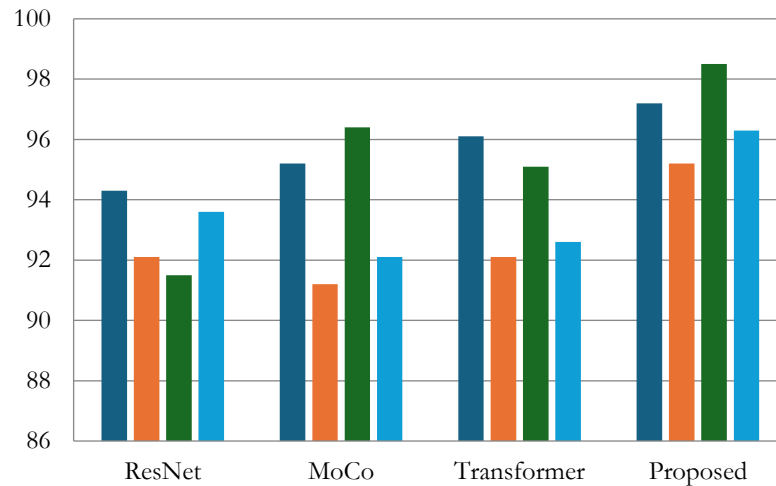


Fig. 7. Comparison results of performance indicators of NACA 4415.

Table 3. Comparison results of performance indicators of NACA 0012.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet	94.3	94.1	92.3	92.6
MoCo	95.2	93.1	94.3	95.2
Transformer	94.2	94.2	94.3	94.3
Proposed	95.9	96.3	98.4	98.6

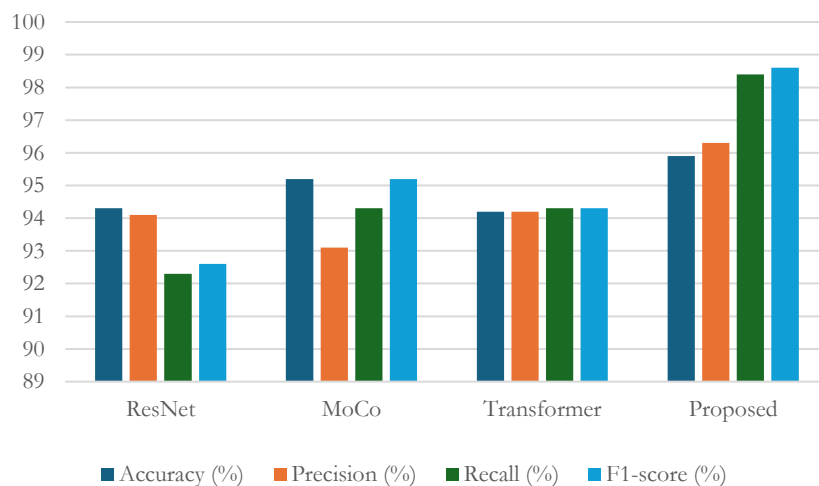


Fig. 8. Comparison results of performance indicators of NACA 0012.

6 | Conclusion

For modelling complex fluid behaviors in aerospace engineering, integration of DL methods in CFD is effective, and it was demonstrated in this study. ML models are widely utilized especially when dealing large CFD datasets, because these ML models greatly reduce the analyzing time without impacting accuracy. Effective prediction of aerospace features like lift, drag, flow separation and turbulence are attained by integrating CNN and PINN in CFD simulations. The potential of this method for real time simulations and design optimization in future aerospace applications is highlighted. For improving accuracy, speed, and scalability of fluid dynamic simulations, this study enhances the potential of ML model to revolutionize

aerospace engineering. Graphs compare the suggested framework with various supervised learning methods such as ResNet, MoCo, and Transformer in terms of accuracy, precision, recall, and F1 score. Different air foils (NACA 2412, NACA 4415, and NACA 0012) under various test conditions were used to evaluate these performance metrics. The graphs showed that the suggested model constantly outperformed others by obtaining the highest recall, accuracy, and F1-scores. The balance between precision, accuracy, and recall for each method is shown using line graphs.

Authors' Contributions

The author was responsible for all stages of the research and manuscript preparation and approved the final version.

Data Availability

All data are included in the text.

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Conflict of Interest

There are no competing interests to declare.

Consent for Publication

The author confirms consent for the publication of this work

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

References

- [1] Deng, Z., Wang, J., Liu, H., Xie, H., Li, B., Zhang, M., ... & Dong, B. (2023). Prediction of transonic flow over supercritical airfoils using geometric-encoding and deep-learning strategies. *Physics of fluids*, 35(7). <https://doi.org/10.1063/5.0155383>
- [2] Cao, Y., Gao, X., & Li, R. (2019). A liquid plug moving in an annular pipe–Heat transfer analysis. *International journal of heat and mass transfer*, 139, 1065–1076. <https://doi.org/10.1016/j.ijheatmasstransfer.2019.05.088>
- [3] Wong, H. S., Chan, W. X., Li, B. H., & Yap, C. H. (2023). Multiple case physics-informed neural network for biomedical tube flows. *ArXiv preprint arxiv:2309.15294*. <https://doi.org/10.48550/arXiv.2309.15294>
- [4] Pathak, J., Subramanian, S., Harrington, P., Raja, S., Chattopadhyay, A., Mardani, M., ... & Anandkumar, A. (2022). *Fourcastnet: A global data-driven high-resolution weather model using adaptive fourier neural operators*. <https://doi.org/10.48550/arXiv.2202.11214>
- [5] Versteeg, H. K. (2007). *An introduction to computational fluid dynamics the finite volume method*, 2/E. Pearson Education India. https://books.google.com/books/about/An_Introduction_to_Computational_Fluid_D.html?id=RvBZ-UMpGzIC
- [6] Wang, R., Kashinath, K., Mustafa, M., Albert, A., & Yu, R. (2020). Towards physics-informed deep learning for turbulent flow prediction. In *Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining* (pp. 1457-1466). <https://doi.org/10.1145/3394486.3403198>

- [7] Najmi, J., Khan, H. A., Javaid, S. S., Hameed, A., & Siddiqui, F. (2024). Aeroelastic tailoring for aerospace applications. *Heliyon*, 10(2). <https://doi.org/10.1016/j.heliyon.2024.e24151>
- [8] Yang, X., Liu, T., & Jia, W. (2025). Research on the aerodynamic-propulsion coupling characteristics of a distributed propulsion system. *Applied sciences*, 15(7), 3536. <https://doi.org/10.3390/app15073536>
- [9] Mbagwu, C. C., Dalle, D. J., & Driscoll, J. F. (2023). Maximizing lift-to-drag and thrust-to-drag ratios for trimmed hypersonic vehicles. *Journal of aircraft*, 60(5), 1564–1576. <https://doi.org/10.2514/1.C037186>
- [10] Guo, H., Yan, Y., Xia, H., Yu, L., & Lv, B. (2022). The prediction and correction method of aircraft static aeroelastic effects: a review of recent progress. *Actuators* (Vol. 11, No. 11, p. 309). MDPI. <https://doi.org/10.3390/act11110309>
- [11] Stanford, B., Chwalowski, P., & Jacobson, K. (2024). Transonic limit cycle oscillations of the benchmark supercritical wing. *International forum on aeroelasticity and structural dynamics* (No. IFASD-2024-20). https://ntrs.nasa.gov/api/citations/20240005090/downloads/IFASD_2024_Bret_Stanford_v3.pdf
- [12] Ghiringhelli, G. L., Lanz, M., & Mantegazza, P. (1990). Active flutter suppression for a wing model. *Journal of aircraft*, 27(4), 334–341. <https://doi.org/10.2514/3.25277>
- [13] Thomas, B. K., Ahmed, Z. U., Al-Abdeli, Y. M., & Matthews, M. T. (2013). The optimisation of a turbulent swirl nozzle using CFD. 271-274. <https://ro.ecu.edu.au/cgi/viewcontent.cgi?article=1397&context=ecuworks2013>
- [14] Serafim, L. P., Freydin, M., & Dowell, E. H. (2023). Flutter and limit-cycle oscillations of a panel using unsteady potential flow aerodynamics. *AIAA journal*, 61(11), 5009–5017. <https://doi.org/10.2514/1.J062943>
- [15] Beck, A., & Kurz, M. (2021). A perspective on machine learning methods in turbulence modeling. *GAMM-mitteilungen*, 44(1), e202100002. <https://onlinelibrary.wiley.com/doi/pdf/10.1002/gamm.202100002>
- [16] Wang, Y. R., & Ma, Y. H. (2024). Application of deep learning models to predict panel flutter in aerospace structures. *Aerospace*, 11(8), 677. <https://doi.org/10.3390/aerospace11080677>
- [17] Negoita, M. F., & Hothazie, M. V. (2024). A machine learning-based approach for predicting aerodynamic coefficients using deep neural networks and CFD Data. *INCAS bulletin*, 16(4). <https://doi.org/10.13111/2066-8201.2024.16.4.9>
- [18] Karali, H., Inalhan, G., & Tsourdos, A. (2024). AI-Driven multidisciplinary conceptual design of unmanned aerial vehicles. In *AIAA SCITECH 2024 Forum* (p. 1708). <https://doi.org/10.2514/6.2024-1708>
- [19] Hasan, M., Redonnet, S., & Zhongmin, D. (2025). Aerodynamic optimization of aircraft wings using machine learning. *Advances in engineering software*, 200, 103801. <https://doi.org/10.1016/j.advengsoft.2024.103801>
- [20] Zan, B. W., Han, Z. H., Xu, C. Z., Liu, M. Q., & Wang, W. Z. (2022). High-dimensional aerodynamic data modeling using a machine learning method based on a convolutional neural network. *Advances in aerodynamics*, 4(1), 39. <https://doi.org/10.1186/s42774-022-00128-8>
- [21] Basem, A., Yasiri, M., Ghodrattallah, P., Sharma, K., Raj, N., Ameer, S. A., ... & Ahmedi, M. (2025). Prediction of the transient coolant jet released from the nose cone at supersonic flow via machine learning. *Scientific reports*, 15(1), 3516. <https://doi.org/10.1038/s41598-025-95429-5>
- [22] Silvestrini, S., & Lavagna, M. (2022). Deep learning and artificial neural networks for spacecraft dynamics, navigation and control. *Drones*, 6(10), 270. <https://doi.org/10.3390/drones6100270>
- [23] Shafi, I., Mazhar, M. F., Fatima, A., Alvarez, R. M., Miró, Y., Espinosa, J. C. M., & Ashraf, I. (2023). Deep learning-based real time defect detection for optimization of aircraft manufacturing and control performance. *Drones*, 7(1), 31. <https://doi.org/10.3390/drones7010031>
- [24] Franz, K., Roscher, R., Milioto, A., Wenzel, S., & Kusche, J. (2018). Ocean eddy identification and tracking using neural networks. In *Igarss 2018-2018 IEEE international geoscience and remote sensing symposium* (pp. 6887-6890). IEEE. <https://doi.org/10.1109/IGARSS.2018.8519261>
- [25] Liu, C., Jiang, R., Wei, D., Yang, C., Li, Y., Wang, F., & Yuan, X. (2022). Deep learning approaches in flow visualization. *Advances in aerodynamics*, 4(1), 17. <https://doi.org/10.1186/s42774-022-00113-1>
- [26] Han, J., Tao, J., & Wang, C. (2018). FlowNet: A deep learning framework for clustering and selection of streamlines and stream surfaces. *IEEE transactions on visualization and computer graphics*, 26(4), 1732–1744. <https://doi.org/10.1109/TVCG.2018.288020>