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Deep Learning for engineering applications

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ABSTRACT

In this paper, we formulate a new artificial intelligence based deep learning formulation to solve engineering applications in domains, heat transfer (2D,3D), strength of materials (2D,3D), design of machine elements, 3D component analysis, 3D assembly analysis, fluid dynamics (2D,3D), Kinematics/Vibrations/control (2D, 3D). Our deep learning based Distributed Artificial Neural Network (DANN) formulation showed six orders of magnitude speed up in computational time and needed an everyday use laptop, not necessitating high end super computer servers for engineering applications analysis. Further, the accuracy of the engineering solution showed 99.9% accuracy and comparable to the conventional existing engineering applications analysis results.

***Keywords**— Deep Learning, Artificial Intelligence, Engineering Applications, Software*

1. INTRODUCTION

Physical quantities such as temperature, stress, fluid velocity, dynamics of a body needs to be predicted on entire spatio-temporal 2D or 3D body to understand or determine the final material property like heat transfer coefficient for thermal application, Young's modulus for stress-strain analysis, coefficient of drag or friction factor from flow velocity, degree of freedom rotations admissible from dynamics simulations in engineering applications [1]. Partial differential equation (PDE) mathematics formulate the basic underlying physical laws which help us calculate such 2D or 3D spatio-temporal profiles that help researchers or engineers predict earlier mentioned physical and material properties [2–5]. Depending on the process, a single PDE or a system of simultaneous, oftentimes called multi-physics PDEs are solved for the same.

Over the last four hundred years PDEs are solved by analytical methods like separation of variables, Fourier series, finding an integral form of the solution, change of variable method to transform the equation to something that is easily solvable. With the advent of numerical methods and high-end computer architecture, PDE mathematics were solved using three extremely powerful and highly successful approaches like finite element method (FEM), finite difference method (FDM), and computational fluid dynamics (CFD) or finite volume method (FVM) [2–5]. Numerical methods like FEM, FDM and FVM iterate the values of the variables of interest a large number of times to satisfy the PDE based formulation of conservation laws to match with the experiments. Such numerical methods need dividing the calculus math into either Fourier series approximations or introducing splines of various degrees of power laws ($1, x, x^2$) to solve. The use of such approaches necessitates the need for fine marching in space or time ($O(\Delta x, \Delta y, \Delta z, \Delta t) << O(1)$) to approximate the PDE formulation to a close accurate solution or also oftentimes called grid or mesh independent solutions. The notion of needing fine grid spacing triggers the user to use thousands to millions of grid points for solving a real world high dimensional problem like a 3D flow over a car or a 3D heat distribution over an electronic cooling chip. This leads to computational inability as such high dimensional matrix inversion costs $O(N^2)$ operations, where N being the number of dimensions. With the present capability of high-performance supercomputing facilities, the time needed to solve such complex and exhaustive matrix inversion calculations is difficult. The solution is yet to be resolved even after we adopt adapative and smart mesh allocation in regions of interest based on the prior knowledge on the given problem. The challenges are continued to be addressed across the globe with google making recent headlines on solving a complex pattern recognition task with revolutionary quantum computing hardware which otherwise would take 10,000 years for a summit supercomputer - the most powerful in the world today - to solve.

Deep Learning was initially introduced as an automatic feature extraction system, requiring minimum pre-processing effort by the user [6, 7]. This is an old technique that has existed from 1940 and is known by different names such as - Cybernetics and Connectionism [6]. It was reintroduced as deep learning in 2007 [7]. The sudden increase in popularity of this field was due to the development of niche algorithms for training these networks. The most popular deep learning models are Convolutional neural network (CNN), which uses images to identify similarities and patterns. They take in image pixel information as input and learn patterns based on the RGB values of the pixels. Advancements in CNN architecture led to the development of sophisticated algorithms such as Recurrent Neural Network (RNN) [7].

2. MATHEMATICAL FORMULATION OF DEEP LEARNING FOR ENGINEERING APPLICATIONS

2.1 Distributed Artificial neural network (DANN)

The input data at each point i and for each sample, j, is trained using Distributed Artificial neural network (DANN), where the activation function is RELU function. The mathematical formulation of DANN is given below.

$$DANN = \forall \oint_{\Omega} \int_{j=1}^{M} \left(h_{j_i} + b_{2_i}\right) dj d\Omega_i \quad (1)$$

$$h_{j_i} = W_{1_i} \cdot h_{j-1_i} + W_{2_i} \cdot x_{j-1_i} + b_{1_i} \quad (2)$$

input, h_{ji} is the hidden cell state and W_{1i}, b_{1i} and W_{2i}, are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, m is the number of training examples The boundary condition for each grid point i, for sample j, is denoted as b_{2i}.

2.2 DANN algorithm

Here, for a given engineering application, analysis, boundary conditions, along with experimental/simulation data is used as training sets to extrapolate the engineering application for the same problem of interest considered. The extrapolated boundary conditions and analysis were tested for 1000% extrapolated conditions. A set of 10 training data sets stored in .csv files are used for the DANN training algorithms and a set of 100s extrapolated test conditions asked in .csv files are tested using DANN testing algorithms. Schematics of the DANN algorithm is shown is Fig. 1.

3. RESULTS

3.1 Heat Transfer (2D, 3D)

Fig. 2 shows the comparison between conventional commercial engineering applications analysis software with our DANN engineering application analysis software, approved, patented and commercially available over https://aidesign.today for heat transfer applications, conduction, convection and radiation applications across various geometries and boundary conditions, Dirichlet and Neumann boundary conditions for 2D and 3D spaces of different geometries.

3.2 Strength of materials (2D,3D)

Fig. 3 shows the comparison between conventional commercial engineering applications analysis software with our DANN engineering application analysis software, approved, patented and commercially available over https://aidesign.today for Strength of materials, to calculate the stress in material across various 2D and 3D spaces of different geometries.

3.3 Design of machine elements

Fig. 3 shows the comparison between conventional commercial engineering applications analysis software with our DANN engineering application analysis software, approved, patented and commercially available over https://aidesign.today for design of machine elements to calculate the stress, material withstanding from breaking and yielding, fracture preventing across different materials and various geometries.

3.4 Kinematics/Dynamics/Vibrations/control (2D, 3D)

Fig. 4 shows the comparison between conventional commercial engineering applications analysis software with our DANN engineering application analysis software, approved, patented and commercially available over https://aidesign.today for design of machine elements to calculate and control the kinematics, dynamics, vibrations for different machine elements and materials across different 2D and 3D geometries.

3.5 Fluid Dynamics (2D, 3D)

Fig. 5 shows the comparison between conventional commercial engineering applications analysis software with our DANN engineering application analysis software, approved, patented and commercially available over https://aidesign.today for fluid dynamics applications of various geometries and solid-fluid interaction analysis for different solid materials, and different fluid materials and properties to calculate and control the fluid dynamics preventing from unstable fluid-solid interaction dynamics, breakage, failure and accidents across different machine elements and components and assemblies and across different full product engineering market available products like submarine and cars.

In all of the above engineering applications analysis, our DANN software analyses the engineering application analysis at six orders of magnitude in a everyday use laptop compared to other commercial engineering applications analysis software commercially available in the market. DANN software for engineering applications is patent approved and available in commercial website for download and use under fee payments and can be accessed from https://aidesign.today.

4. CONCLUSION

In this paper, we formulate a new artificial intelligence based deep learning formulation to solve engineering applications and developed a patent approved DANN algorithm software for commercial use across engineering applications and industries. Our DANN formulation is six orders of magnitude faster than any other commercial engineering applications analysis software commercially available in the market. Further, our DANN formulation solves the engineering application analysis using an everyday use laptop, not necessitating high end super computer servers for engineering applications analysis. Also, the accuracy of our DANN formulation for engineering application analysis is 99.9% accuracy and comparable to the conventional existing engineering applications analysis results. Furthermore, our DANN formulation is patent approved and is commercially available in commercial website for download and use under fee payments and can be accessed from https://aidesign.today.

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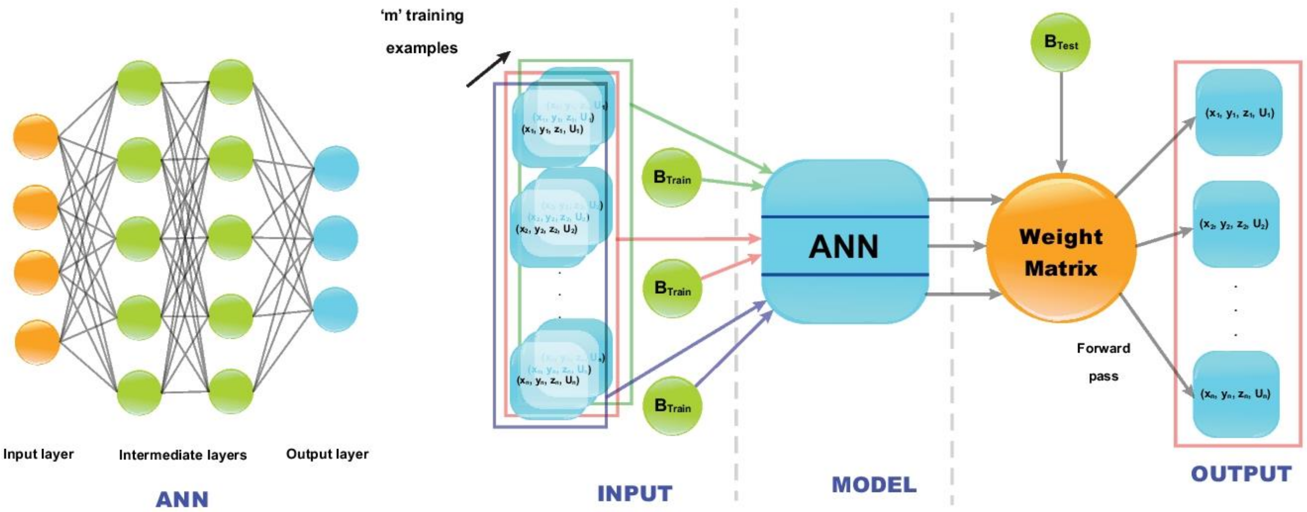

Fig. 1: Schematics of mathematical formulation of Distributed Artificial neural network (DANN).

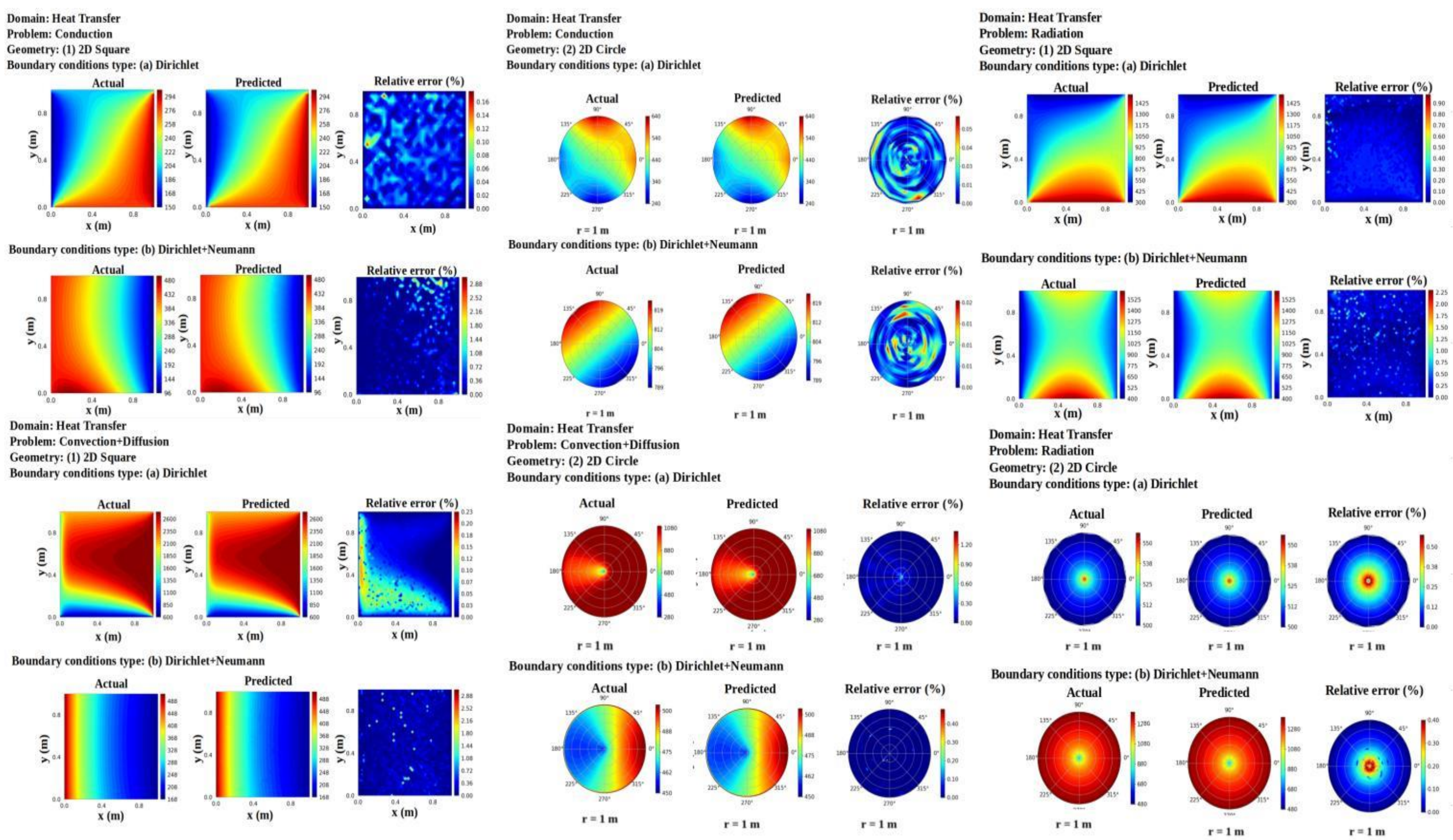

Fig. 2: Comparison of Heat transfer application between commercial conventional engineering application analysis software with our DANN formulation AIDESIGN software can be accessed and downloaded and use under fee payments from https://aidesign.today

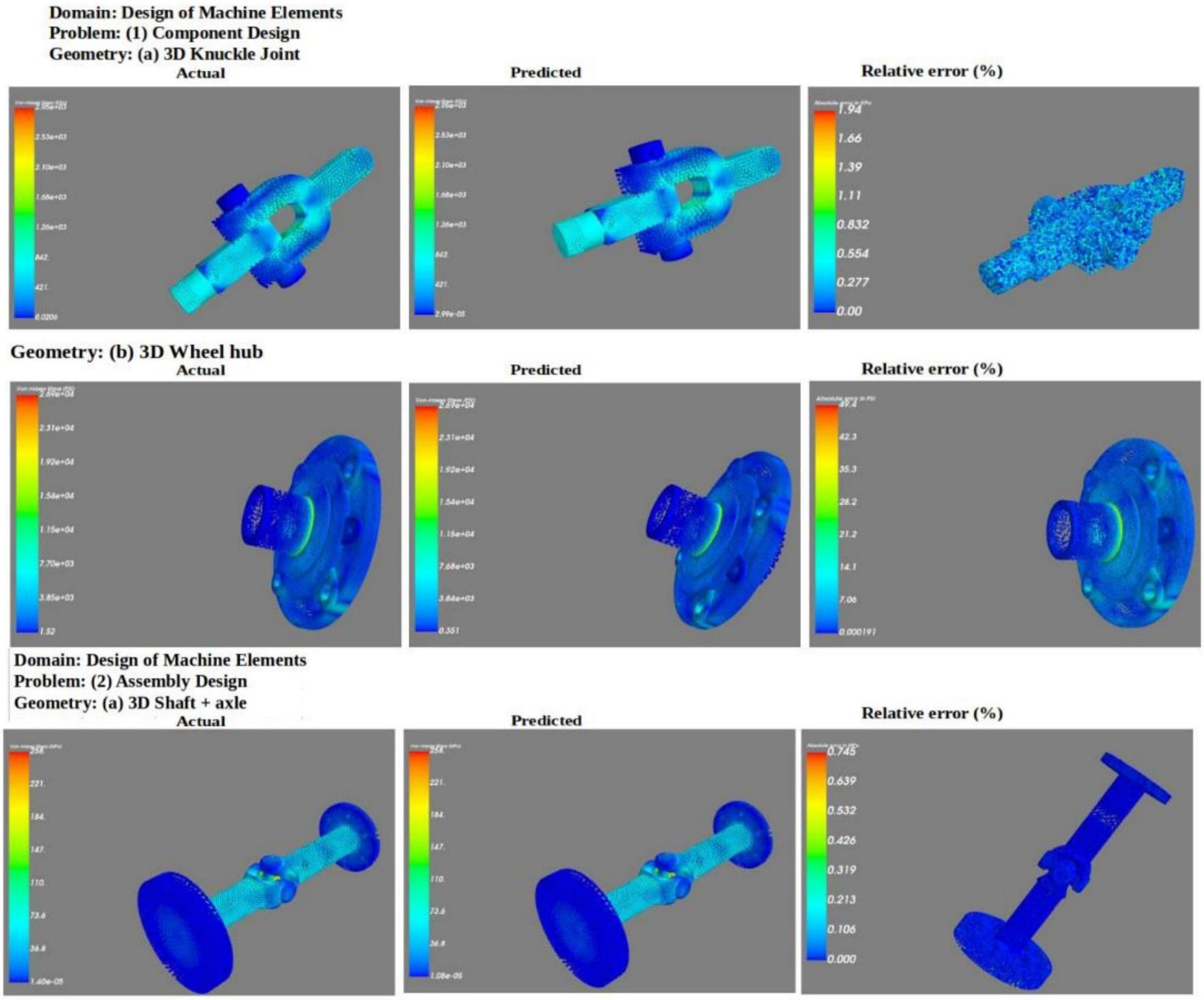

Fig. 3: Comparison of Design of machine elements application between commercial conventional engineering application analysis software with our DANN formulation AIDESIGN software can be accessed and downloaded and use under fee payments from https://aidesign.today

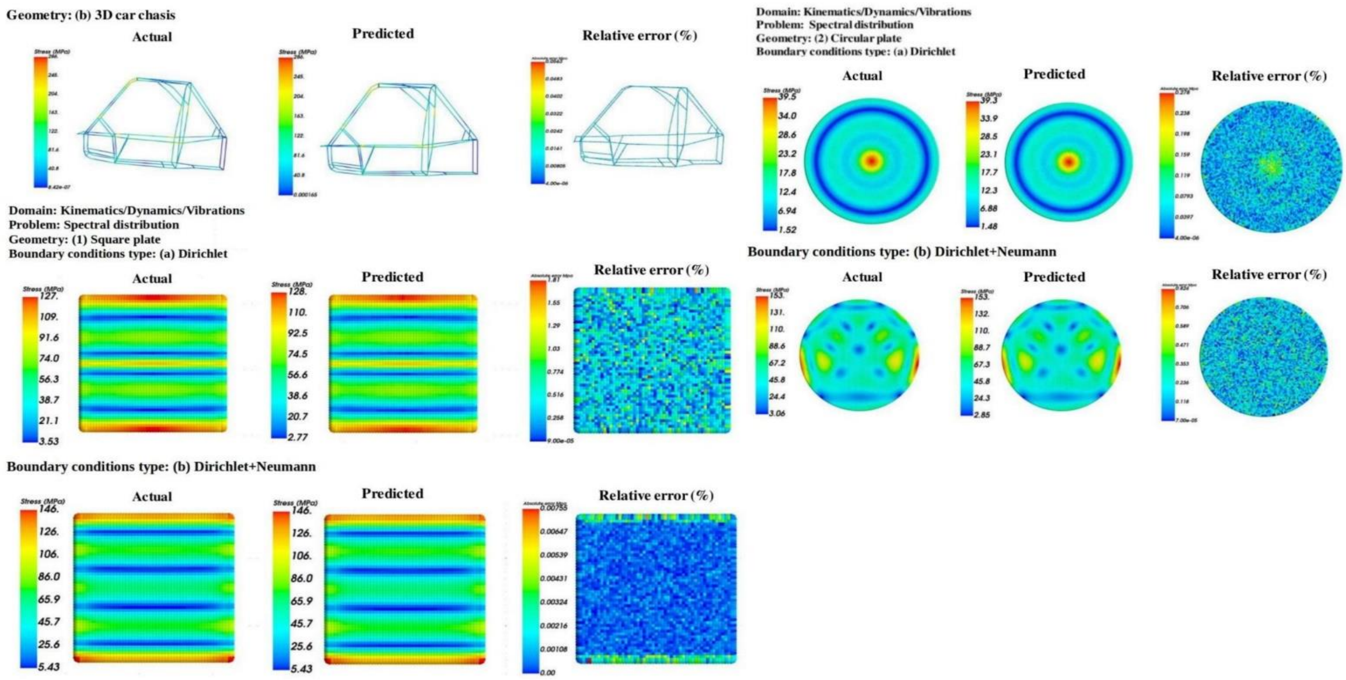

Fig. 4: Comparison of Design of machine elements and Kinematics/Dynamics/Vibrations between commercial conventional engineering application analysis software with our DANN formulation AIDESIGN software can be accessed and downloaded and use under fee payments from https://aidesign.today

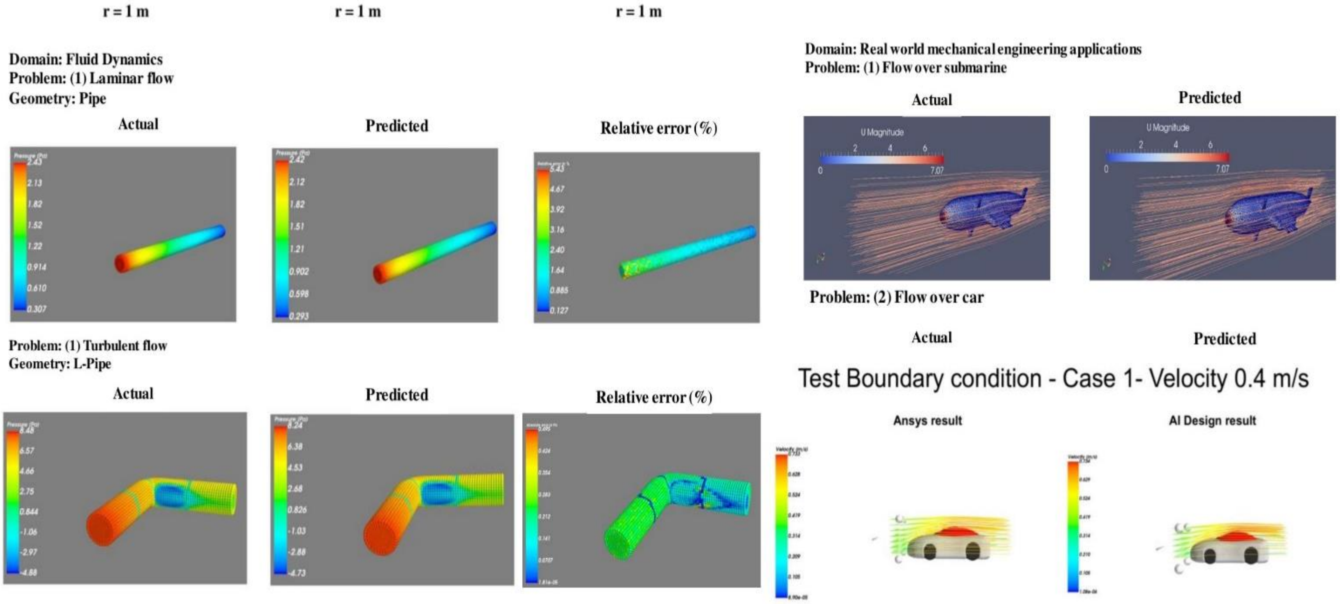

Fig. 5: Comparison of Fluid dynamics for real products and commercially available full products and industries application between commercial conventional engineering application analysis software with our DANN formulation AIDESIGN software can be accessed and downloaded and use under fee payments from https://aidesign.today

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