In the matter of The Patents Act, 1970
and
In the matter of The Patents Rules, 2003
And

In the matter of Indian Patent Application 201941036792 dated **12 October 2019**

Response to Examiner Objections in the Office Action dated December 2, 2021

We, **Indian Institute of Technology Madras (IIT Madras),** Office of the Dean ICSR, Chennai – 600036, India, the applicant in the above application herein submit as follows in response to the Examiner objections in the FER dated **December 2, 2021**.

AMENDMENTS:

A. To merely expedite prosecution in the subject application and without acquiescing to the rejections, the pending independent claims 1 and 13 are amended. The claims 1 and 13 are narrowed down by reciting the elements in dependent claims 7, 9 and 11, claims 7, 9 and 11 stand cancelled. Support for the amendments is found at least in [0049], [0051] and [0053] of the specification. No new matter has been added.

Amended Claim 1 of the instant application disclosesa method of solving a heat transport problem over an object characterized by geometry. The method uses a hardware multi-threading process. The hardware includes a processor configured to run a training model, a first number of storage process units configured to store input data, a second number of memory operation units configured to store output data, and a hardware switch configured to minimize idle time of the processor. The method steps are as follows. A geometry and associated boundary conditions are provided and the geometry is discretized into a grid having a number of grid points. The temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at each grid point is specified. A heat flow equation selected from one of conduction, convection or radiation for the geometry and the associated boundary conditions to obtain a temperature, or a heat flow rate, or both at each grid point is solved at steady state and the

solution for each grid point is stored in a training database. Using the training database a training model is selected. The training models are three novel deep learning models that include Point by Point Recurrent **Neural Network (PPRNN), a Distributed Recurrent Neural Network (DRNN) or a Distributed Artificial Neural network (DANN) model. the PPRNN model is given by** $PPRNN = \oint_{\Omega} \int_{j=1}^{M} tanh(h_{j_i} + b_{2_i}) dj d\Omega_i$, **the DRNN model is given by:** $DRNN = \forall \oint_{\Omega} \int_{j=1}^{M} tanh(h_{j_i} + b_{2_i}) dj d\Omega_i$ **and the DANN model is given by** $DANN = \forall \begin{cases} 0 \ if \ x \le 0 \\ \int_{j=1}^{M}(h_j + b_2) dj \ if \ x > 0 \end{cases}$, **where,** $h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1 x$ **is the input,** *h* **is the hidden cell state and** W_1, b_1**and** W_2, **are the weight and bias matrices for hidden-hidden and input-hidden connections, and M is the number of examples for training, tanh is an activation function and** Ω **is the domain of interest**. Further the modified boundary condition or initial condition or both associated with the geometry is given as input and,a temperature, a heat flow rate or both are generated at each grid point corresponding to the modified boundary condition or initial condition.

Amended claim 13 now discloses a system for solving a heat transport problem over an object characterized by a geometry. The system includes a hardware switch and a processor coupled to the hardware switch to run a neural network engine. The processor is configured to receive a geometry and associated boundary conditions and discretize the geometry into a grid, that has a number of grid points, receive temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at each grid point, solve a heat flow equation selected from one of conduction, convection or radiation for the geometry and the associated boundary conditions to obtain a temperature, or a heat flow rate, or both at each grid point at steady state. The solution is stored for each grid point in a training database and a model selected from a PPRNN, a DRNN or a DANN model is trained using the training database.

The PPRNN model is given by $PPRNN = \oint_{\Omega} \int_{j=1}^{M} tanh(h_{j_i} + b_{2_i}) dj d\Omega_i$, **The DRNN model is given by:** $DRNN = \forall \oint_{\Omega} \int_{j=1}^{M} tanh(h_{j_i} + b_{2_i}) dj d\Omega_i$ **and the DANN model is given**

by:

$$DANN = \forall \begin{cases} 0 \; if \; x \leq 0 \\ \int_{j=1}^{M} (h_j + b_2) \, dj \; if \; x > 0 \end{cases} \text{where} \, h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1 \text{, } x \text{ is the input, h is the}$$

hidden cell state and W1, b1 and W2, are the weight and bias matrices for hidden-hidden and input-hidden connections, and M is the number of examples for training Ω is the domain of interest, and tanh is an activation function. The processor is further configured to receive a modified boundary condition or initial condition or both associated with the geometry as input to the trained model andgenerate a temperature, a heat flow rate at both at each grid point corresponding to the modified boundary condition or initial condition.

OBJECTION(1)–NOVELTY: Claim(s) (1-17) lack(s) novelty, being anticipated in view of disclosure in the document cited above under reference D1: US20170032068A1 and D2: JP6516081B1

B. **D1 US20170032068A1** teaches about a simulation application which generates simulation parameters associated with a simulation which includes geometry associated with the simulation and corresponding boundary conditions. The simulation engine processes the simulation parameters and generates a solution using neural network. The simulation engine then executes a finite element analysis solver using the solution estimate as a starting point. A solution estimate comprises an approximate solution for the simulation, and warm-starts a finite element analysis (FEA) solver. The process adapted by D1 is as follows. Mapping engine receives simulation parameters from an end-user. Simulation parameters include geometry and boundary conditions. Geometry represents a structure or combination of structures within which one or more physical processes may occur. Upon receipt of simulation parameters, mapping engine implements a convolutional neural network (CNN) to map simulation parameters to a solution estimate. Solution estimate includes a set of values that represent an approximate solution for the simulation. As mentioned above, solution estimate may include different values depending on the type of simulation to be generated. CNN within mapping engine may have any technically feasible network architecture. During training, CNN would adjust weights within each different layer in order to associate specific geometrical features and/or boundary conditions of the sample simulations with certain portions of the corresponding converged solutions. Once mapping engine generates solution estimate, FEA solver generates the simulation using simulation parameters and solution estimate.FEA solver provides converged solution to display engine.

Display engine then causes display device to display converged solution to the end-user.

C. Amended claim 1 over D1:Amended claim 1 claims a multithreaded process. Hardware multi-threading allows multiple threads to share the RNN operation to each processor in an overlapping fashion to try to utilize the hardware resources efficiently. The utilization of the processor was increased with no idle wait time for calculating individual data point i.D1 does not teach a multi-threading process. Secondly, the method of the claimed invention uses PPRNN, DRNN or DANN as training models. D1 does not disclose these training models instead D1 uses a Finite Element Analysis (FEA) solver. The PPRNN, DRNN or DANN methods are novel and produce results that are superior to FEA. A comparison between truth (finite element numerical solution) and predicted (PPRNN solution) for square geometry domain radiation with Dirichlet boundary condition is illustrated in FIG. 13A – FIG. 13C. A comparison between truth (finite element numerical solution) and predicted (PPRNN solution) for circular geometry domain radiation with Neumann boundary condition (B) is illustrated in FIG. 14A – FIG. 14C. Table. 2 comprises the performance comparison (simulation time) of FDM and the claimed methods PPRNN, DRNN and DANN for heat conduction, heat convection and heat radiation on square and circular plate geometries and Dirichlet and Neumann boundary conditions.

201941036792	D1: US 2017/0032068 A1
1. A method 200 of solving a heat transport problem over an object characterized by a geometry, using a hardware multi-threading process, the hardware comprising: a processor configured to run a training model, a first number of storage process units configured to store input data, a second number of memory operation units configured to store output data, and a hardware switch configured to minimize idle time of the processor, the method comprising:	1. Finite element analysis (FEA) is a tool that can be used to simulate a variety of different physical processes. For example, FEA may be applied to simulate heat transfer through a structure. Typically, an FEA simulation includes a mesh of distinct nodes that are coupled together and a system of governing equations that describe how the distinct nodes interact with one another. In the above heat transfer example, the structure could be represented as a triangular mesh of distinct nodes, and heat transfer equations would describe how heat is exchanged between adjacent nodes within the triangular mesh.

Providing (201) a geometry and associated boundary conditions and discretizing the geometry into a grid, wherein the grid comprises a number of grid points; specifying (202) temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at each grid point;	As described in greater detail below in conjunction with FIG. 2, simulation application **120** is configured to receive from an end-user simulation parameters associated with a simulation to be generated. The simulation parameters include geometry associated with the simulation and corresponding boundary conditions. The simulation could be a fluid dynamics simulation, a thermal simulation, a material simulation, an electromagnetic simulation, and so forth. Simulation engine **120** processes the simulation parameters and then, using a neural network, generates a solution estimate. The solution estimate could reflect an estimated velocity vector field in the case of a fluid dynamics simulation, an estimated temperature distribution in the case of a thermal simulation, an estimated stress/strain distribution in the case of a materials simulation, or an estimated electromagnetic field in the case of an electromagnetic simulation. Based on the estimated solution, simulation engine **120** then executes an FEA solver using the solution estimate as a starting point. The FEA solver iteratively solves a set of governing equations associated with the simulation until a converged solution is reached. The converged solution is then provided to the end-user.

solving (203) a heat flow equation selected from one of conduction, convection or radiation for the geometry and the associated boundary conditions to obtain a temperature, or a heat flow rate, or both at each grid point at steady state;	Starting from the Solution estimate, causing the FEA Solver to iteratively solve a set of governing equations associated with the simulation to generate a converged solution for the simulation.
storing (204) the solution for each grid point in a training database;	FIG. 2 is a more detailed illustration of the simulation application of FIG. 1, according to various embodiments of the present invention. As shown, simulation application **120** includes a mapping engine **210**, an FEA solver **220**, and a display engine **230**. **Database 122 includes training data 240.**
training (205) a model selected from a PPRNN, a DRNN or a DANN model using the training database;	*Not disclosed*
the PPRNN model is given by: $$PPRNN = \oint_{\Omega} \int_{j=1}^{M} tanh\big(h_{j_i} + b_{2_i}\big)dj\,d\Omega_i$$ where $$h_{j_i} = W_{1_i} \cdot h_{j-1_i} + W_{2_i} \cdot x_{j-1_i} + b_{1_i}$$ x is the input, h is the hidden cell state and W_1, b_1 and W_2, b_2 are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;	*Not disclosed*

	Not disclosed
the DRNN model is given by: $$DRNN = \forall \oint_{\Omega} \int_{j=1}^{M} tanh\big(h_{j_i} + b_{2_i}\big)djd\Omega_i$$ where, $$h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1$$ x is the input, h is the hidden cell state and W_1, $b_1$and W_2, are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;	
the DANN model is given by: $$DANN = \forall \begin{cases} 0 \; if \, x \leq 0 \\ \int_{j=1}^{M} \big(h_j + b_2\big)dj \, if \, x > 0 \end{cases}$$ where, $h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1$ x is the input, h is the hidden cell state and W_1, $b_1$and W_2, are the weight and bias matrices for hidden-hidden and input-hidden connections, and M is the number of examples for training	Not disclosed
inputting (206) a modified boundary condition or initial condition or both associated with the geometry; and	Not disclosed
generating (207) a temperature, a heat flow rate at both at each grid point corresponding	Not disclosed

to the modified boundary condition or initial condition.	

D. Amended claim 13 over D1: Amended claim 13 now discloses a system for solving a heat transport problem over an object characterized by a geometry. The system includes a hardware switch and a processor coupled to the hardware switch to run a neural network engine. The discloses a multi-threaded process for solving the heat transport problem.D1 does not teach a multi-threaded system. Also the claimed system involves novel techniques such as PPRNN, DRNN and DANN as training models. D1 teaches a finite element analysis (FEA) simulation model, which is different from the techniques claimed in the invention. Further the performance comparison of the finite method and the claimed techniques are shown in Table. 2, which clearly indicates that the claimed system is technically advanced over the system taught in D1. The table below illustrates the feature comparison between the claimed system and the system taught in D1.

201941036792	D1: US 2017/0032068 A1
13. A system for solving a heat transport problem over an object characterized by a geometry, the system comprising:	1. Finite element analysis (FEA) is a tool that can be used to simulate a variety of different physical processes. For example, FEA may be applied to simulate heat transfer through a structure. Typically, an FEA simulation includes a mesh of distinct nodes that are coupled together and a system of governing equations that describe how the distinct nodes interact with one another. In the above heat transfer example, the structure could be represented as a triangular mesh of distinct nodes, and heat transfer equations would describe how heat is exchanged between adjacent nodes within the triangular mesh.
a hardware switch (**102**);	

a processor (**101**) coupled to the hardware switch (**102**) to run a neural network engine, wherein the processor (**101**) is configured to:	
13.receive a geometry and associated boundary conditions and **discretize the geometry into a grid, wherein the grid comprises a number of grid points;**	Upon receipt of **simulation parameters, mapping engine implements** a convolutional neural network (CNN) **to** map simulation parameters **to** a solution estimate.
receive temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at **each grid point**;	*Not Disclosed*
solve a heat flow equation selected from one of conduction, convection or radiation for the geometry and the associated boundary conditions to obtain a temperature, or a heat flow rate, **or both at each grid point at steady state;**	*Not Disclosed*
store the solution for each grid point in a training database;	
train a model selected from a PPRNN, a DRNN or a DANN model using the training database;	*Not disclosed*
the PPRNN model is given by: $$PPRNN = \oint_{\Omega} \int_{j=1}^{M} tanh\left(h_{j_i} + b_{2_i}\right) dj\, d\Omega_i$$ where	*Not disclosed*

$h_{j_i} = W_{1_i} \cdot h_{j-1_i} + W_{2_i} \cdot x_{j-1_i} + b_{1_i}$ x is the input, h is the hidden cell state and W_1, b_1 and W_2, b_2 are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;	
the DRNN model is given by: $$DRNN = \forall \oint_{\Omega} \int_{j=1}^{M} tanh(h_{j_i} + b_{2_i})djd\Omega_i$$ where, $h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1$ x is the input, h is the hidden cell state and W_1, b_1 and W_2, are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;	*Not disclosed*
the DANN model is given by: $$DANN = \forall \begin{cases} 0 \, if \, x \leq 0 \\ \int_{j=1}^{M} (h_j + b_2)dj \, if \, x > 0 \end{cases}$$ where, $h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1$ x is the input, h is the hidden cell state and W_1, b_1 and W_2, are the weight and bias	*Not disclosed*

matrices for hidden-hidden and input-hidden connections, and M is the number of examples for training	
receive a modified boundary condition or initial condition or both associated with the geometry as input to the trained model; and,	*Not disclosed*
generate a temperature, a heat flow rate at both at each grid point corresponding to the modified boundary condition or initial condition.	*Not disclosed*

E.**D2 JP6516081B1** discloses a method of analysis wherein the physical quantities in each area are based on the volume of the assembly area and the boundary surface characteristic quantity, which are quantities **that do not require the quantity that defines the geometrical shape**. It can be calculated. Therefore, it is possible to calculate the physical quantity without giving the calculation data model an amount that defines the geometric shape of the aggregation region. Therefore, by using this embodiment, it is sufficient to create a calculation data model having at least the volume of the aggregation region and the boundary surface characteristic amount (the area of the boundary surface and the normal vector of the boundary surface) in the pre-processing. Physical quantities can be calculated without creating a calculation data model having quantities that define geometrical shapes. This disclosure uses the discretization governing equation derived based on this idea, and unlike the conventional numerical analysis methods, such as a finite element method and a finite volume method, it does not depend on geometric shape. In addition to these effects, the present embodiment enables model degeneracy by enabling calculation in an aggregation region that assembles divided regions. Here the volume of the divided region and the boundary surface characteristic amount are amounts that do not require an amount defining the specific geometric shape of the divided region. The process disclosed is as follows

F. **Amended claim 1 over D2:** Amended claim 1 discloses a method 200 of solving a heat transport problem over an object characterized by geometry. The method includes providing geometry and associated boundary conditions and discretizing the geometry into a grid having a

number of grid points. The temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at each grid point is specified. A heat flow equation selected from one of conduction, convection or radiation for the geometry and the associated boundary conditions to obtain a temperature, or a heat flow rate, or both at each grid point is solved at steady state and the solution for each grid point is stored in a training database. Using the training database a training model is selected. The training models include PPRNN, DRNN and DANN. These are not taught in D2. D2 do not depend on the geometry or boundary conditions as disclosed in the claimed invention instead the physical quantities in each area are based on the volume of the assembly area and the boundary surface characteristic quantity. Hence the teachings in D2 are entirely different from the claimed invention. The applicant humbly objects the mention of D2 as prior art for the invention because the method taught on D2 is entirely different from the claimed Claim 1 and is novel.

201941036792	D2:JP6516081B1
1. A method 200 of solving a heat transport problem over an object characterized by a geometry, using a hardware multi-threading process, the hardware comprising: a processor configured to run a training model, a first number of storage process units configured to store input data, a second number of memory operation units configured to store output data, and a hardware switch configured to minimize idle time of the processor, the method comprising:	1. A simulation method for numerically analyzing physical quantities in physical phenomena with a computer, The computer divides the analysis area into a plurality of divided areas, The governing equation in the discretized divided area derived by the weighted residual integration method using only coordinates of the vertices of the divided area (Vertex) and an amount that does not require connectivity of the vertices (Connectivity) On the basis of the volume of each of the divided areas and the divided area characteristic quantities indicating the characteristics of the divided areas adjacent to each other, the coordinates (Vertex) of the vertices of the divided areas
Providing (201) a geometry and associated	The connectivity information (Connectivity) of

boundary conditions and discretizing the geometry into a grid, wherein the grid comprises a number of grid points; specifying (202) temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at each grid point;	the vertices are not required.
solving (203) a heat flow equation selected from one of conduction, convection or radiation for the geometry and the associated boundary conditions to obtain a temperature, or a heat flow rate, or both at each grid point at steady state;	Generate a data model for calculation in the divided area having By aggregating a plurality of divided areas, a required number of aggregated areas are generated, The governing equation in the discretized set area derived by the weighted residual integration method using only coordinates of the vertices of the set area (Vertex) and an amount that does not require connectivity of the vertices (Connectivity) On the basis of the volume of each of the collective areas and the collective area characteristic quantities indicating the characteristics of the collective areas adjacent to each other, the coordinates of the vertices of the collective area (Vertex) and the connectivity information of the apex are not required. Generate a data model for calculation in the set area having Based on the physical property values in the analysis region and the calculation data model in the collection region, the conductance representing the characteristics of movement of the physical amount between the collection regions and out of the analysis region, and the physical amount of each collection region And

	calculating a capacitance representing a characteristic of accumulation.
storing (204) the solution for each grid point in a training database;	*Not disclosed*
training (205) a model selected from a PPRNN, a DRNN or a DANN model using the training database;	*Not disclosed*
the PPRNN model is given by: $$PPRNN = \oint_{\Omega} \int_{j=1}^{M} tanh\big(h_{j_i}$$ $$+ b_{2_i}\big)djd\Omega_i$$ where $$h_{j_i} = W_{1_i} \cdot h_{j-1_i} + W_{2_i} \cdot x_{j-1_i} + b_{1_i}$$ x is the input, h is the hidden cell state and W_1, b_1 and W_2, b_2 are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;	*Not disclosed*
the DRNN model is given by: $$DRNN = \forall \oint_{\Omega} \int_{j=1}^{M} tanh\big(h_{j_i}$$ $$+ b_{2_i}\big)djd\Omega_i$$ where, $$h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1$$	*Not disclosed*

x is the input, h is the hidden cell state and W_1, b_1 and W_2, are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;	
the DANN model is given by: $$DANN = \forall \begin{cases} 0 \, if \, x \leq 0 \\ \int_{j=1}^{M} (h_j + b_2) dj \, if \, x > 0 \end{cases}$$ where, $h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1$ x is the input, h is the hidden cell state and W_1, b_1 and W_2, are the weight and bias matrices for hidden-hidden and input-hidden connections, and M is the number of examples for training	*Not disclosed*
inputting (206) a modified boundary condition or initial condition or both associated with the geometry; and	*Not Disclosed*
generating (207) a temperature, a heat flow rate at both at each grid point corresponding to the modified boundary condition or initial condition.	*Not Disclosed*

G. Amended claim 13 over D2: Amended claim 13 now discloses a system for solving a heat transport problem over an object characterized by a geometry. The system includes a hardware switch and a processor coupled to the hardware switch to run a neural network engine. D2 does not teach a multi-threaded system. D2 do not depend on the geometry or boundary conditions as disclosed in the claimed invention instead the physical quantities in each area are based on the

volume of the assembly area and the boundary surface characteristic quantity. Hence the teachings in D2 are entirely different from the claimed invention. The applicant humbly suggests that claim 13 is novel and requests the controller to remove the objection. The difference of the subject-matter of the claims of the present application from the cited documentD2 is shown in the tabular format. The applicant humbly requests the controller to remove the objection of novelty as the present invention has novel features as compared to prior art.

201941036792	D2:JP6516081B1
13. A system for solving a heat transport problem over an object characterized by a geometry, the system comprising:	1. A simulation method for numerically analyzing physical quantities in physical phenomena with a computer, The computer divides the analysis area into a plurality of divided areas, The governing equation in the discretized divided area derived by the weighted residual integration method using only coordinates of the vertices of the divided area (Vertex) and an amount that does not require connectivity of the vertices (Connectivity) On the basis of the volume of each of the divided areas and the divided area characteristic quantities indicating the characteristics of the divided areas adjacent to each other, the coordinates (Vertex) of the vertices of the divided areas
a hardware switch (**102**);	
a processor (**101**) coupled to the hardware switch (**102**) to run a neural network engine, wherein the processor (**101**) is configured to:	

receive a geometry and associated boundary conditions and **discretize the geometry into a grid, wherein the grid comprises a number of grid points;**	And in this embodiment, the point which is calculating the physical quantity without using the quantity which specifies **geometric shape in the solver processing differs from the conventional finite volume method greatly**, and this point is a big feature of this embodiment. is there. Such features are obtained in the solver process by using discretized governing equations that use only quantities that do not require geometrically defined quantities.
receive temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at **each grid point;**	*Not Disclosed*
solve a heat flow equation selected from one of conduction, convection or radiation for the geometry and the associated boundary conditions to obtain a temperature, or a heat flow rate, **or both at each grid point at steady state;**	*Not Disclosed*
store the solution for each grid point in a training database;	
train a model selected from a PPRNN, a DRNN or a DANN model using the training database;	*Not disclosed*
the PPRNN model is given by: $$PPRNN = \oint_{\Omega} \int_{j=1}^{M} tanh\big(h_{j_i} + b_{2_i}\big)djd\Omega_i$$	*Not disclosed*

where

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

x is the input, h is the hidden cell state and W_1, b_1 and W_2, b_2 are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;

the DRNN model is given by: $$DRNN = \forall \oint_{\Omega} \int_{j=1}^{M} tanh(h_{j_i} + b_{2_i})djd\Omega_i$$ where, $$h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1$$ x is the input, h is the hidden cell state and W_1, b_1 and W_2, are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;	*Not disclosed*
the DANN model is given by: $$DANN = \forall \begin{cases} 0 \, if \, x \leq 0 \\ \int_{j=1}^{M} (h_j + b_2)dj \, if \, x > 0 \end{cases}$$ where, $h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1$ x is the input, h is the hidden cell state and	*Not disclosed*

W_1, b_1 and W_2, are the weight and bias matrices for hidden-hidden and input-hidden connections, and M is the number of examples for training	
receive a modified boundary condition or initial condition or both associated with the geometry as input to the trained model; and,	*Not Disclosed*
generate a temperature, a heat flow rate at both at each grid point corresponding to the modified boundary condition or initial condition.	*Not Disclosed*

OBJECTION(2)–INVENTIVE STEP: Claim(s) (1-17) lack(s) inventive step, being obvious in view of teaching (s) of cited document(s) above under reference D1, D2 and common general knowledge for the following reasons:Subject matter of claims 1-17 under consideration lacks inventive step and do not constitute an invention under section 2(1)(j) of The Patents Act, 1970 (as amended), because D1 and/or D2 discloses "a method of solving a heat transport problem over an object characterized by a geometry using a hardware multi-threading process.The method includes geometry and associated boundary conditions and discretizing the geometry into a grid.The method includes specifying temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at each grid point. A heat flow equation selected from one of conduction, convection or radiation for the geometry is selected and associated boundary conditions, is solved using a known method such as analytical, FDM or FEM to obtain a temperature at each grid point..............."(refer D1,abstract, claims, paragraph no.[0027]-[0032],[0037]-[0041], fig.5) (refer D2, the whole document) and also itwould have been obvious to a person skilled in the art having regards to the common general knowledge in theart to reach to the alleged invention.

H. Amended claims 1 and 13 over D1 and D2: Amended claims 1 and 13 claims for a method and system of solving a heat transport problem over an object characterized by geometry. The method uses a hardware multi-threading process.Hardware multi-threading allows multiple threads to share the RNN operation to each processor in an overlapping fashion to try to

utilize the hardware resources efficiently with no idle wait time for calculating the individual data point i. D1 or D2 does not teach a multi-threading process. Secondly, the method of the claimed invention uses PPRNN, DRNN or DANN as training models. These methods are unique. The number are training samples are reduced when compared to the prior arts. D1 does not disclose these training models instead D1 uses a Finite Element Analysis (FEA) solver. D2 does not involve a method that uses geometry. The physical quantity in D2 is calculated without using the quantity which specifies geometric shape in the solver processing .Such features are obtained in the solver process by using discretized governing equations that use only quantities that do not require geometrically defined quantities. D2 is an entirely different method.The PPRNN, DRNN or DANN methods as claimed in the instant application are novel and produce results that are superior to FEAas taught in D1. A comparison between truth (finite element numerical solution) and predicted (PPRNN solution) for square geometry domain radiation with Dirichlet boundary condition is illustrated in FIG. 13A – FIG. 13C. A comparison between truth (finite element numerical solution) and predicted (PPRNN solution) for circular geometry domain radiation with Neumann boundary condition (B) is illustrated in FIG. 14A – FIG. 14C. Table. 2 comprises the performance comparison (simulation time) of FDM and the claimed methods PPRNN, DRNN and DANN for heat conduction, heat convection and heat radiation on square and circular plate geometries and Dirichlet and Neumann boundary conditions. The max error of various thermal management application are represented in Table. 3. Errors are largely reduced in the claimed method. A person skilled in the art may not be able to arrive at the claimed invention by combining D1 and D2 or by considering the teachings in D1 or D2 because none of D1 or D2 teaches a multi-threading process or teaches the PPRNN, DRNN or DANN methods. In view of the above submission both the cited references either alone or in combination do not disclose or suggest the claimed features. Hence claim 1 and claim13 are inventive. The applicant requests the controller to remove the objection.

OBJECTION(3)– NON PATENTABILITY

(I) The Examiner states that Claim(s) (1-17) are statutorily non-patentable under the provision of clause (k) of Section 3 for the following reasons: Without prejudice to aforementioned objections U/S 2(1)(j), the subject matter of claims 1-17 which relate to a device for "Machine learning, deep learning and artificial intelligence for physical transport phenomenon in thermal

management" prima facie falls within scope of clause (k) of section (3) of the Patents Act, 1970 (as amended). Claims 1-12 are method claims executing steps as: providing, specifying, solving, storing, training, inputting, generating, which are a set of predefined sequence of steps used to implement an algorithm, without disclosing any functional limitations pertaining to the enablement of said features as claimed in form of method steps. Moreover, the claimed technical implementation does not go beyond a generic technical implementation as such technical considerations must go beyond merely finding a computer algorithm to carry out some procedure and the method steps as claimed herein are completed or done with the help of computer executable instructions in form of a pre-defined sequential manner. Hence, all above steps are done with the help of computer program in terms of an algorithm and performed on computing device and that its implementation is trivial in form of an algorithm. Claims 13-17 are system claims which relate to electronic computing system but do not disclose any functional and structural limitations of the feature of the said claims but in turn represents computer program per se (readable instructions with the help of algorithm) in sequential manner and implemented on the hardware (conventional systems) and software environment with certain protocols (algorithms) without exhibiting any hardware orientation/dependence for collective and collaborative implementation and not going beyond the "normal" physical interactions between the program (software) and the computer (hardware) on which it is run in form of a computer program. So, the said system claims represent a set of instructions executed on a general purpose and conventional computer/processor/computing platform, which attracts computer program per-se. Moreover, the subject matter as claimed 3-5 and 7-12 of the alleged invention seeks to protect mathematical expression calculations as there is output realization from predefined set of inputs calculated through a specific mathematical expression for dictionary estimation. The subject matter of the said claims merely specify the technical nature of the features so claimed in the purview of data to be used with the said mathematical expression or parameters of the mathematical expression necessary for implementing the same on a particular set of data and thereby calculating the output in a predefined manner. Hence, all above steps are done with the help of computer program in terms of an algorithm and performed on computing device and are mathematical expression calculation in their pristine form. Therefore, these claims as such relate to "mathematical expressions" and are considered to be falling under section 3(k) the Indian Patents Act, 1970 (as amended). Therefore, the claims 1-17 are considered to be falling under the

scope of section 3(k) the Patents Act, 1970 (as amended) and hence not allowable. Therefore, the invention claimed in said claims is not patentable.

I.The Applicant humbly denies the controller's contentions that claims 1-17 are non-patentable under Section 3(k) of the Patents Act, 1970. Section 3(k) recites as:

(k) a mathematical or business method or a computer programme per se or algorithms;

The Applicant respectfully submits that the subject-matter of claims of the present application is purely technical in nature and does not relate to a computer program *per se*. The system presented in Claims 1-17 is not just an algorithm or a computer program per se that is merely executed/implemented by a computing device, as the said system involves an object characterized by a geometry and having a boundary and includes physical components such as **a hardware switch that responds to instructions received from the processor.** The hardware switch 102 may execute a multi-threading process on receiving instructions from the processor to solve the transport problem while minimizing idle time of the processor.Further the system also includes a **communication unit and a display.**

It is submitted that the problem solved in the instant invention is a heat flow transport problem across a geometrical object having a boundary.The method uses a hardware multi-threading process. The hardware includes a processor configured to run a training model, a first number of storage process units configured to store input data, a second number of memory operation units configured to store output data, and a hardware switch configured to minimize idle time of the processor. The method includes providing a geometry and associated boundary conditions and the geometry is discretized into a grid having a number of grid points. The temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at each grid point is specified. A heat flow equation selected from one of conduction, convection or radiation for the geometry and the associated boundary conditions to obtain a temperature, or a heat flow rate, or both at each grid point is solved at steady state and the solution for each grid point is stored in a training database. Using the training database a training model is selected. The training models are three novel deep learning models from PPRNN, DRNN and DANN. Also the performance of the claimed deep learning models from PPRNN, DRNN and DANN is compared with the performance of prior art methods. The claimed methods are faster and have reduced error. Hence, the present invention provides a technical solution by reciting the features as claimed in the present invention.

In *FeridAllanivs Union Of India &Ors*, the judge has opined *"Moreover, Section 3(k) has a long legislative history and various judicial decisions have also interpreted this provision. **The bar on patenting is in respect of `computer programs per se....' and not all inventions based on computer programs. In today's digital world, when most inventions are based on computer programs, it would be retrograde to argue that all such inventions would not be patentable**. Innovation in the field of artificial intelligence, blockchain technologies and other digital products would be based on computer programs, however the same would not become nonpatentable inventions - simply for that reason. It is rare to see a product which is not based on a computer program. Whether they are cars and other automobiles, microwave ovens, washing machines, refrigerators, they all have some sort of computer programs in-built in them**. Thus, the effect that such programs produce including in digital and electronic products is crucial in determining the test of patentability."***

Further, it is submitted that the present invention complies with the official requirements set forth by the Hon'ble Delhi High Court in in the case of Telefonaktiebolaget LM Ericsson v. Intex Technologies (India) Limited (CS(OS) No.1045/ 2014, dated March 13, 2015). The order holds that, *'Thus, it appears to me prima facie that any invention which has a technical contribution or has a technical effect and is not merely a computer program per se as alleged by the defendant and the same is patentable.'*

Based on the aforementioned opinion of the High Court, the present invention answers the following questions in affirmative:-

• goes beyond normal interaction between programme and the hardware: *providing (201) a geometry and associated boundary conditions and discretizing the geometry into a grid, wherein the grid comprises a number of grid points; specifying (202) temperature or heat flow conditions at the boundary surrounding the geometry and an initial condition at each grid point; solving (203) a heat flow equation selected from one of conduction, convection or radiation for the geometry and the associated boundary conditions to obtain a temperature, or a heat flow rate, or both at each grid point at steady state; storing (204) the solution for each grid point in a training database;*

• affects a change in the functionality/ performance of existing hardware- *training (205) a model selected from a PPRNN, a DRNN or a DANN model using the training database,*

wherein

the PPRNN model is given by:

$$PPRNN = \oint_{\Omega} \int_{j=1}^{M} tanh(h_{j_i} + b_{2_i})djd\Omega_i ....(4)$$

where

$$h_{j_i} = W_{1_i} \cdot h_{j-1_i} + W_{2_i} \cdot x_{j-1_i} + b_{1_i}.....................(5)$$

x is the input, h is the hidden cell state and W_1, b_1 and W_2, b_2 are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;

the DRNN model is given by:

$$DRNN = \forall \oint_{\Omega} \int_{j=1}^{M} tanh(h_{j_i} + b_{2_i})djd\Omega_i ....(7)$$

where,

$$h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1.....................(8)$$

x is the input, h is the hidden cell state and W_1, b_1 and W_2, are the weight and bias matrices for hidden-hidden and input-hidden connections, Ω is the domain of interest, M is the number of examples for training, tanh is an activation function;

the DANN model is given by:

$$DANN = \forall \begin{cases} 0 \, if \, x \leq 0 \\ \int_{j=1}^{M} (h_j + b_2)dj \, if \, x > 0 \end{cases} ....10)$$

where,

$$h_j = W_1 \cdot h_{j-1} + W_2 \cdot x_{j-1} + b_1.....................(8)$$

x is the input, h is the hidden cell state and W_1, b_1 and W_2, are the weight and bias matrices for hidden-hidden and input-hidden connections, and M is the number of examples for training;

• capable of bringing further technical effect- The hardware switch 102 may execute a multi-threading process on receiving instructions from the processor to solve the transport

problem while minimizing idle time of the processor. The method 400 may further involve obtaining the weight and bias matrices for the PPRNN model by minimizing mean square error between the predicted and input temperatures for each mesh independent point i for an example m given by $MSE_i = \frac{1}{m}\sum_{n=1}^{m}|T_{Pred_i} - T_{Act_i}|^2$. The method 400 may further involve obtaining the weight and bias matrices of the DRNN model by minimizing mean square error between the predicted and input temperatures for each mesh independent point i for an example m given by: $MSE_i = \sum_{n=1}^{m}||T_{Pred} - T_{Ac}||^2$, The method 400 may further involve obtaining the weight and bias matrices by minimizing mean square error between the predicted and input temperatures for each mesh independent point i for an example m given by equation $MSE_i = \frac{1}{m}\sum_{n=1}^{m}|T_{Pred_i} - T_{Act_i}|^2$. In view of the above submissions, the applicant respectfully submits that the present invention is not attracted under section 3(k).

OBJECTION(5)– DEFINITIVENESS:

(I) The Examiner states that Claim(s) 1-17 do not sufficiently define the invention for the reasons as follows: 1. The expression "one or more" and "plurality" are used in the claims should be replaced by some other suitable term to make these claims clear and definite.

J. The claims are amended and the terms "one or more" and "plurality" are removed.

OBJECTION(6)– OTHER REQUIREMENTS:

(I) The Examiner states that the vague and imprecise statement in terms of the expression "spirit" in the description in the last paragraph implies that the subject-matter for which protection is sought may be different to that defined by the claims, thereby resulting in a lack of clarity of the claims when the description is used to interpret the claims. Such statement should therefore be amended to remove this inconsistency.

K. The statement is part of boiler plate language. However the term "spirit" is removed. A marked copy of amended specification is submitted.

III. FORMAL REQUIREMENTS:

1. The Examiner states that date and sign of applicant/agent should be present at the end of claims as per Form 2 Para 6 of Indian Patent Act 1970.

L. The date is inserted at the end of claims, the signature is present at the end of claims.The complete specification is uploaded.

1.. The Examiner states that details regarding application for Patents which may be filed outside India from time to time for the same or substantially the same invention should be furnished within Six months from the date of filing of the said application under clause(b) of sub section(1) of section 8 and rule 12(1) of the Patent Act,1970.

M. A PCT application was made on 12th October 2020. An updated Form 3 was filed on 26th November 2021. Updated form 3 with petition is filed along with the response.

2. Details regarding the search and/or examination report including claims of the application allowed, as referred to in Rule 12(3) of the Patent Rule, 2003, in respect of same or substantially the same invention filed in all the major Patent offices along with appropriate translation where applicable, should be submitted within a period of Six months from the date of receipt of this communication as provided under section 8(2) of the Patents Act,1970.

N. Updated Form 3 is filed to meet the requirement.

1. The Examiner states that If any amendment is necessitated in the complete specification then it is required to clearly identify (submission of marked copy) the amendments carried out and to indicate the portion (page no and line no) of the complete specification as filed on which these amendments are based on. Further the pages wherever amendments are carried out need to be freshly typed on white pages and to be filed in duplicate.
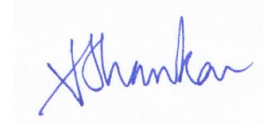
O. The marked copy of the complete specification is filed. Also the amended pages are freshly typed on white pages and are filed in duplicate.

2. Reference numerals should be supplemented in parenthesis to enhance the intelligibility of Claims and clearly define the scope of the invention, in accordance with section 10(4)(c) of The Patents Act 1970 as amended by the Patents (Amendment) Act 2005.

P. The reference numerals of the physical components and the method steps are inserted in parenthesis.

No new matter has been added in addressing the technical objections, either in the amended claims, specification or drawings. Applicants therefore respectfully request grant of the patent at an early date.

Dated this 1st Day of June, 2022.

(Dr.V.SHANKAR)
IN/PA-1733
For and on behalf of the Applicants

To
The Controller of Patents
The Patent Office at Chennai