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Input to State Stable Learner Based Neural Control of Nonlinear Aircraft Dynamics

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ABSTRACT

This research presents a novel work on learner-based neural network control structure for stabilizing nonlinear aircraft dynamics along longitudinal and lateral path using *Input-to-State Stability (ISS)*. Neural networks approximated anonymous aerodynamic forces, whereas ISS-based responses guaranteed bounded state trajectories under external disruptions such as wind and turbulence. Simulation results using MATLAB exhibits effective stabilization of pitch and roll motions, accurate neural approximation of nonlinear forces of an aircraft and strenuous performance of the proposed controller.

1. Introduction

Nonlinear aircraft dynamics has practical challenges for control and stability due to complex aerodynamic forces, conjoin with longitudinal and lateral motions, and external disturbances such as wind gusts or turbulences. The Standard controllers gives substandard outputs while robust performance across the aerodynamics, with vast nonlinearities, can be achieved by neural network. Neural network-based control techniques have been used to compensate for unknown nonlinear dynamics and enhance control robustness of aircraft.

Neural networks provide a systematic tool for approximating unknown functions in nonlinear systems. In the matter of aircraft control, they can learn the relation between aircraft states and nonlinear aerodynamic forces, entitle real-time compensation without requiring a intense analytical model. Feedforward neural networks are pertinent for this task, as the aerodynamic forces predominantly depend on the current states rather than the previous values.

Input-to-State Stability (ISS) offers a meticulous framework for ensuring that the system states remain certain in the presence of bounded disturbances and model approximation errors. By unifying neural network estimates with ISS-based feedback, it is possible to assure robust stability while recompensing for unknown nonlinearities. This method discrete the tasks of learning and control: the neural network approximates the nonlinear forces offline, while the ISS controller ensures bounded closed-loop behavior.

We propose a learner based neural network control structure for both longitudinal and lateral aircraft dynamics using ISS. Feedforward neural networks approximate aerodynamic loads, and ISS-based feedback ensures bounded state trajectories in spite of nonlinearities and disturbances. The potential of the proposed approach is demonstrated through simulations that uphold stabilization of pitch and roll motions and robustness against approximation errors and external disturbances.

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2. Literature Review

The Contemporary studies have extensively focused on neural network-based control strategies for nonlinear dynamic systems, notably in aircraft dynamics. Adaptive neural control methods have been successfully applied to dynamic systems for robust tracking performance under uncertainty [1], while specified performance based neural controllers have been created for robot manipulators to improve transient and steady-state behavior [2]. Learning-based approaches have also been extended to quadrotor systems to handle time-varying and coupling uncertainties effectively [3]. Furthermore, learner based dynamic programming merged with neural networks has been used for robust control of nonlinear multi-agent systems with vagueness [4], and neural-network-based model predictive and dynamic flight control methods have been widely employed to stringent feedback and nonlinear systems to enhance stability and performance [5], [10]. These advancements highlight the significant role of neural networks in learner based control design for intricate dynamical systems.

Concurrently, notable progress has been made in input-to-state stability (ISS) theory for nonlinear, time-delay, stochastic, and hybrid systems. ISS properties have been exmined for impulsive control systems using automated mechanisms to manage nonlinear disturbances [14], whereas the global exponential ISS result were designed for systems with mixed time delays [15]. Lyapunov–Krasovskii approaches are applied to characterize ISS in neutral systems [16], and fixed-time ISS frameworks were proposed for stochastic nonlinear systems to guarantee fast convergence [17]. Fractional-order ISS control were also studied for fuzzy systems under cyberattacks [18], and ISS extensions formulated for perturbed gradient flows in learner based control settings [19]. Additionally contributions include ISS analysis for systems with delays using predictor based control [20], infinite-dimensional systems over Banach spaces [21], discrete-time Lur'e systems [22], and finite or fixed-time convergence frameworks [23]. Current researches also explore ISS verification using Koopman operator models [24], linear time-varying systems [25], Markov jump

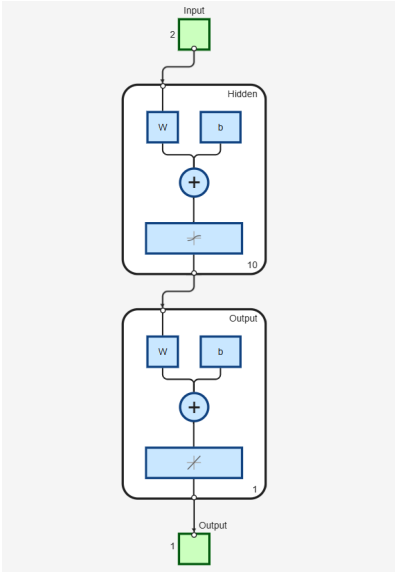

Figure 1: Neural Network Structure

systems [26], switched stochastic delay systems [27], and physics-guided neural networks with ISS guarantees [28], showing the high applicability of ISS theory in modern control systems

3. Mathematical Model for Aircraft Longitudinal and Lateral Dynamics

The nonlinear longitudinal dynamics of the aircraft are represented as

$$\dot{\zeta}_1 = \zeta_2, \tag{1}$$
$$\dot{\zeta}_2 = f_L(\zeta) + u_a + d_\varsigma, \tag{2}$$

where $\zeta_1 = \theta$ is the pitch angle, $\zeta_2 = q$ is the pitch rate, u_a is the aileron control input, $f_L(\zeta)$ represents unknown nonlinear aerodynamic forces in longitudinal direction, and d_ς is a bounded external disturbances.

Similarly, the nonlinear lateral-directional dynamics of the aircraft can be represented as

$$\dot{\eta}_1 = \eta_2, \tag{3}$$
$$\dot{\eta}_2 = f_{Lat}(\eta) + u_e + d_\varsigma, \tag{4}$$

where $\eta_1 = \phi$ is the roll angle, $\eta_2 = p$ is the roll rate, u represents the elevator control input, $f_{Lat}(\eta)$ represents unknown nonlinear aerodynamic lateral forces, and d_ς is a bounded external disturbances. The aim of the neural network model is to approximate $f_L(\zeta)$ and $f_{Lat}(\eta)$ so that the control input can compensate for nonlinear aerodynamic effects assuring bounded aircraft states under the structure of Input-to-State Stability.

The neural network borders on the nonlinear aerodynamic functions using a feedforward structure:

$$\hat{f}(x) = W_2\, tanh(\Sigma(W_1 x + b_1)) + b_2, \tag{5}$$

where x takes the values of $\zeta_L = [\theta, q]^T$ as the input vector for longitudinal dynamics and $\eta_{Lat} = [\phi, p]^T$ as the input vector for lateral dynamics, W_1 and W_2 are weight matrices, b_1 and b_2 are biases, and $tanh(\Sigma(W_1 x + b_1))$ is a nonlinear activation function taken as it leads to faster convergence. The network is trained offline using a dataset generated from synthetic aircraft states and related aerodynamic forces. The resulting $\hat{f}_L(\zeta) and \hat{f}_{Lat}(\eta)$ provides a real-time estimate of the unknown nonlinear dynamics during flight simulation.

4. Methodology

The proposed methodology focuses on maintaining equilibrium state of nonlinear aircraft dynamics in both longitudinal and lateral directions using a learner-based neural network unified with *Input-to-State Stability*. The system states for the longitudinal motion are defined as $\zeta_L = [\theta, q]^T$, where θ is the pitch angle and q is the pitch rate, with the elevator deflection u_e as the control input. For lateral motion, the states are defined as $\eta_{Lat} = [\phi, p]^T$, where ϕ is the roll angle and p is the roll rate, with the aileron or rudder input u_a. Unknown nonlinear aerodynamic forces in both longitudinal and lateral directions are approximated using feedforward neural networks, while external disruptions such as wind gusts are treated as bounded inputs to satisfy ISS requirements.

In the initial stage, the nonlinear dynamics of the aircraft are designed. For longitudinal motion, the dynamics are expressed as

$$\dot{\zeta}_1 = \zeta_2, \tag{6}$$
$$\dot{\zeta}_2 = f_L(\zeta) + u_a + d_\varsigma, \tag{7}$$

where $f_L\zeta)$ represents the unknown longitudinal nonlinear forces and d_ς is a bounded disturbances. Similarly, the lateral-directional dynamics are taken as

$$\dot{\eta}_1 = \eta_2, \tag{8}$$
$$\dot{\eta}_2 = f_{Lat}(\eta) + u_e + d_\varsigma, \tag{9}$$

where $f_{Lat}(\eta)$ represents the unknown lateral nonlinear forces and d_ς is a bounded disturbances. Synthetic datasets are generated by sampling the state variables within realistic performance envelopes of an aircraft and evaluating the corresponding nonlinear forces for training the neural networks.

In the next stage, feedforward neural networks are trained offline to approximate the unknown nonlinear functions $f_L(\zeta)$ and $f_{Lat}(\eta)$. The network outputs are defined as

$$\hat{f}(x) = W_2\, tanh(\Sigma(W_1 x + b_1)) + b_2 \tag{10}$$

where x is the input state vector, W_1 and W_2 are the weight matrices, b_1 and b_2 are the biases, and $tanh(\Sigma(W_1 x + b_1))$ is a nonlinear activation function leads to faster convergence.

The third stage involves the design of an ISS-based feedback controller for both longitudinal and lateral motions. To combine the neural network into the ISS structure, the approximation error is defined as

$$\Delta(x) = f(x) - \hat{f}(x), \tag{11}$$

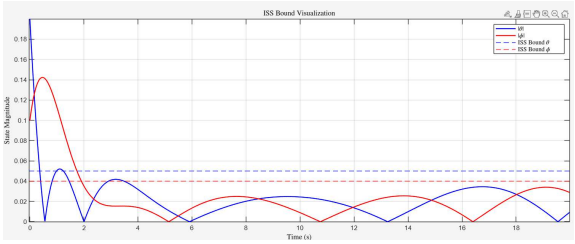

Figure 2: ISS bound

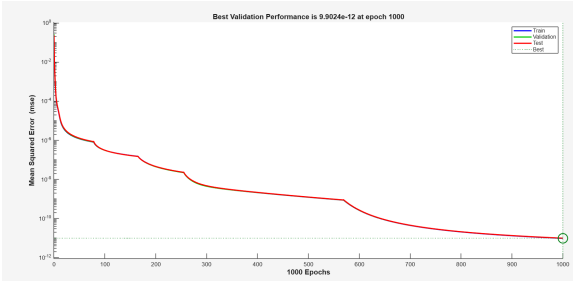

Figure 3: Neural Network Performance

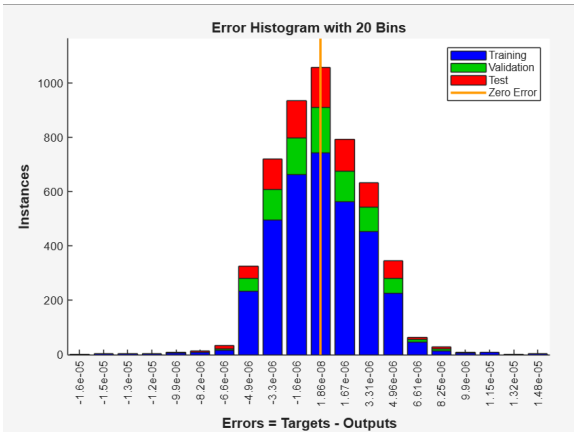

Figure 4: Error Histogram

presumed to be bounded by $|\Delta(x)| \leq \delta_1$. The aircraft dynamics with the neural estimate taken into the control law

$$u = -Kx - \hat{f}(x) \tag{12}$$

become

$$\dot{x} = (A - BK)x + B\Delta(x) + Bd_{\varsigma}, \tag{13}$$

In the expression $A - BK$, the term indicates the stabilized linear component of the lateral and longitudinal systems, whereas $B\Delta(x) + Bd_{\varsigma}$ is categorized as a bounded disturbance input. The ISS condition ensures that when both $\Delta(x)$ and d_{ς} are bounded, the state $x(t)$ stays within the limits defined by the constraint inequality below

$$|x(t)| \leq Ce^{-\lambda t}|x(0)| + \gamma(|\Delta(x) + d_{\varsigma}|) \tag{14}$$

here

$$\gamma(|\Delta(x) + d_{\varsigma}|) = \frac{|\Delta(x) + d_{\varsigma}|}{|1 + \Delta(x) + d_{\varsigma}|}, \tag{15}$$

$C > 0, \lambda > 0$ and $\gamma(|\Delta(x) + d_{\varsigma}|)$ is a class-$\mathcal{K}$ function and x takes the values of $\zeta_L = [\theta, q]^T$ as the input vector for longitudinal dynamics and $\eta_{Lat} = [\phi, p]^T$ as the input vector for lateral dynamics as defined earlier.

The neural network serves as a disturbance compensator, it turn down the effective nonlinear forces acting on the system, whilst the feedback term $-Kx$ ensures convergence of states. By treating the approximation error $\Delta(x)$ as a bounded input, the ISS structure guarantees that the system remains stable without requiring online neural weight adaptation or Lyapunov-based stability analysis. This independent task allows robust stabilization of the nonlinear aircraft system with a learner-based neural model.

The control law is given by

$$u = -Kx - \hat{f}(x), \tag{16}$$

where K is the feedback gain matrix to balance the linearized system. The automatic control dynamics is expressed as

$$\dot{x} = (A - BK)x + B\Delta(x) + Bd_{\varsigma} \tag{17}$$

where $\Delta(x)$ and d_{ς} are bounded, ensuring that the system satisfies the ISS property. This secures that all states remain bounded while during the nonlinearities and external disturbances.

The neural network values, state trajectories, control inputs, and approximation errors are observed to validate the performance of the ISS-based controller. Phase portraits of the states are also analyzed to demonstrate boundedness and convergence, emphasizing the robustness of the proposed learner-based neural control structure for nonlinear aircraft dynamics.

5. Results and Discussion

Simulation studies were implemented to evaluate the efficacy of the proposed learner-based neural network controller with ISS for both longitudinal and lateral aircraft dynamics. The neural networks were trained on synthetic datasets covering the operational parameters, evaluating accurate approximations of the unknown nonlinear aerodynamic forces. The ISS-based feedback controller make use of these estimates to balance the aircraft states under bounded disturbances.

5.1. Longitudinal Dynamics

The longitudinal simulation show that both the pitch angle θ and pitch rate q converge to their desired equilibrium values in spite of the presence of nonlinearities and external disturbances. The neural network accurately approximates the longitudinal aerodynamic forces, and the approximation

Table 1
Neural Network Approximation Errors

Direction	Maximum Error	Minimum Error	Mean Error	RMS Error
Longitudinal	6.8119×10^{-6}	0	2.7147×10^{-6}	2.8888×10^{-6}
Lateral	6.2037×10^{-6}	0	2.2078×10^{-6}	2.5752×10^{-6}

Table 2
ISS Based State Deviations

State	Maximum Deviation	Minimum Deviation	Mean Deviation	RMS Deviation
θ	0.2	3.30×10^{-6}	0.022394	0.029271
q	0.5	2.52×10^{-5}	0.04286	0.074516
ϕ	0.14231	2.85×10^{-5}	0.025707	0.038408
p	0.2	1.63×10^{-5}	0.033813	0.043137

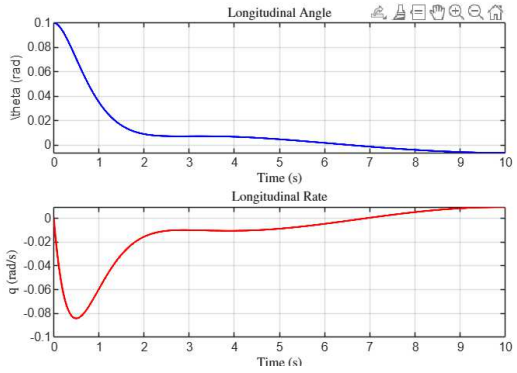

Figure 5: Longitudinal States

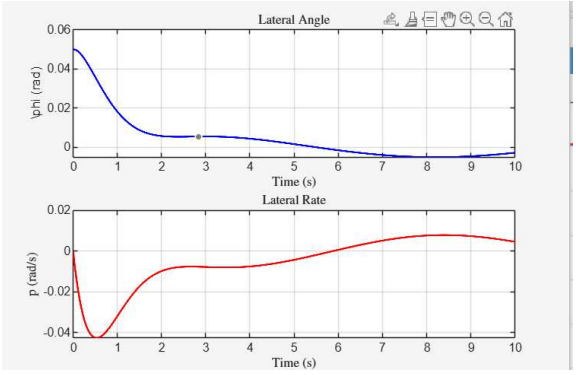

Figure 6: Lateral States

errors $\Delta_L(x)$ remains substantial throughout the simulation. The control input (elevator deflection) remains within expected margins, showing that the controller achieves effective boundedness without uncontrolled actuation.

5.2. Lateral Dynamics

In parallel, for lateral directional dynamics, the roll angle ϕ and roll rate p are within the limits subject to the ISS-based control law. The neural network values are close to the unknown lateral forces with small bounded error, make sures the feedback controller recompense effectively for nonlinearities. The control input (ailerons/rudder) remains smooth and bounded, and the phase portrait of ϕ vs p confirms convergence towards the equilibrium position, proving the ISS property. The turnout results show that the combination of neural network approximation and ISS-based feedback provides robust stabilization for nonlinear aircraft dynamics in both longitudinal and lateral directions.

Table 3
Neural network estimates vs True forces and ISS errors

Time Sampled	θ	q	$f_L$true	f_LNN	Δ_L	ϕ	p	f_{Lat}true	f_{Lat}NN	Δ_{Lat}
0	0.2	-0.5	0.30008	0.3016	-0.00151520000	0.1	0.2	-0.17999	-0.17985	-0.00014382000
1	-0.050441	-0.05266	0.067347	0.067319	0.00002829700	0.1131	-0.11066	0.03224	0.032448	-0.00020848000
2	-0.0002984	0.029865	-0.023743	-0.023741	-0.00000178410	0.035247	-0.084802	0.045263	0.045263	0.00000010129
3	0.04104	-0.041234	0.012468	0.012483	-0.00001483600	0.015548	-0.040694	0.022267	0.022264	0.00000258010
4	0.031875	-0.064388	0.035573	0.035579	-0.00000654940	0.014022	-0.032961	0.017464	0.017461	0.00000230950
5	0.013222	-0.046558	0.030636	0.030636	-0.00000031006	0.002301	-0.021539	0.014157	0.014157	0.00000007721
6	-0.0011382	-0.019522	0.016186	0.016186	0.00000011657	-0.013436	0.0039332	0.0026211	0.0026244	-0.00000331600
7	-0.01222	0.0078924	-0.00020389	-0.00020407	0.00000017789	-0.02323	0.029461	-0.011331	-0.011327	-0.00000393180
8	-0.020173	0.031767	-0.015327	-0.015328	0.00000099819	-0.0245	0.042451	-0.019916	-0.019912	-0.00000398830
9	-0.024259	0.046812	-0.025321	-0.025322	0.00000183880	-0.018912	0.039113	-0.019814	-0.01981	-0.00000421910
10	-0.024422	0.049677	-0.027531	-0.027533	0.00000180030	-0.0089537	0.022532	-0.012191	-0.012188	-0.00000294550
11	-0.02088	0.040667	-0.022093	-0.022094	0.00000088488	0.0030024	-0.00029434	-0.00099492	-0.00099481	-0.00000011173
12	-0.013681	0.022991	-0.011552	-0.011552	-0.00000015071	0.014539	-0.021311	0.0091019	0.0090997	0.00000217280
13	-0.0030495	0.0013419	0.00045121	0.00045174	-0.00000053027	0.022951	-0.034083	0.014678	0.014676	0.00000250960
14	0.0099144	-0.019415	0.010574	0.010575	-0.00000083967	0.025431	-0.035509	0.014684	0.014682	0.00000225220
15	0.022789	-0.035205	0.016769	0.016772	-0.00000317190	0.019989	-0.026111	0.010282	0.010279	0.00000250930
16	0.032074	-0.043267	0.018577	0.018584	-0.00000744670	0.0068197	-0.0092394	0.0037397	0.0037389	0.00000081231
17	0.034212	-0.042313	0.016744	0.016753	-0.00000893700	-0.010731	0.010142	-0.0028069	-0.0028038	-0.00000304970
18	0.027065	-0.03252	0.012484	0.012489	-0.00000505350	-0.026576	0.02663	-0.008011	-0.0080075	-0.00000344260
19	0.011193	-0.015515	0.0068152	0.0068164	-0.00000115520	-0.033983	0.035439	-0.011214	-0.011213	-0.00000136350

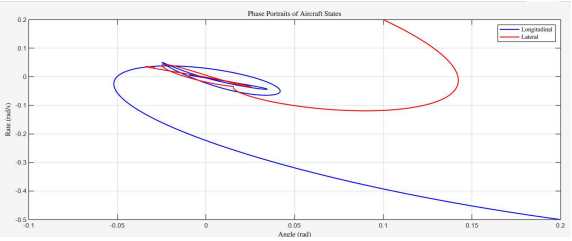

Figure 7: Phase portraits of aircraft system

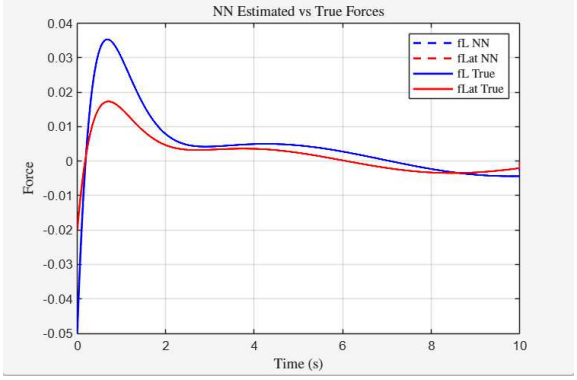

Figure 8: Neural Network Estimated vs True Forces

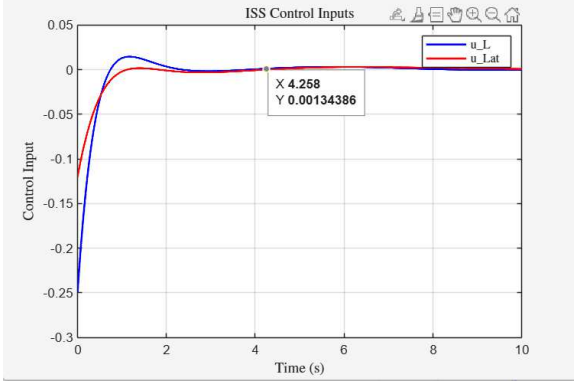

Figure 9: ISS Control Inputs

The neural networks act as disturbance equalizers, reducing the pressure on the feedback controller and upgrading the overall performance.

The uniformly bounded error, together with ISS design, makes sure that the states remain within predictable limits even under external disturbances, explaining the robustness and reliability of the proposed structure. Phase portraits and trajectory plots shows that all states are stabilized effectively, featuring the effectual neural network learning and ISS based control.

6. Conclusions

Overall, the proposed methodology shows that learner-based neural networks integrated with ISS can control nonlinearities and disturbances in aircraft dynamics, providing a practical and robust solution for stabilizing both longitudinal and lateral motions. The proposed study elaborates the effectiveness of ISS-based neural network control stabilizing both longitudinal and lateral dynamics of a nonlinear aircraft under bounded disturbances. By applying feedforward neural networks to estimate the unknown nonlinear aerodynamic forces and integrating them with a simple ISS-based feedback control law, the aircraft states were maintained within confined limits without requiring Lyapunov-based adaptation or online weight tuning. The simulations, including wind disturbances and NN approximation errors, confirm that the ISS framework robustly secures the stability while recompense for nonlinearities, and the Neural Network provides accurate estimation of aerodynamic forces.

Mainly, this approach features the feasibility of learner-based neural control integrated with ISS for real-time aircraft stabilization. The results indicate that the proposed methodology can effectively reduce the impact of model variability and external disturbances, making it a forward approach for future research in learner based intelligent flight control systems.

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8. Funding Declaration

This research received no funding.

9. Data Availability Declaration

The synthetically generated data using neural network were used in this research.The synthetic dataset generated and analyzed in this research will be provided by the corresponding author upon request.

10. Competing Interests Declaration

The authors declare that they have no competing interests.

11. Author Contribution Declaration

The corresponding author, Sowmiya K, did the conceptualization,designing the mathematical model, data analysis, writing, and figure preparation of the research paper.The Co-authors, Radha Gupta and Rose Bindu Joseph reviewed and supervised the final draft of the research paper.

12. Consent to Participate Declaration

Not applicable.

13. Ethics and Consent to Publish Declaration

Not applicable.

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