Comparison of Neural Networks vs Human Brain Learning Rate and Accuracy Under Complex Influences using SDM

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Abstract. This research focus on the comparative learning process of neural networks and human brain, exploring the accuracy trends influenced by parameters like noise complexity, learning speed and decay frequency. Using a System Dynamics Model (SDM), the simulation of evolution of neural network and human accuracy over time. Results reveal that neural networks demonstrate rapid learning with high variability, while humans exhibit slower yet steadier improvement. An ANOVA analysis and T-test confirms significant differences in learning behaviors between systems, as well as strong interaction effects over time. While correlation test shows relationship in both these System's sub-factors. By, using ARIMA forecasting model the stabilization for both systems i.e. Human and Neural Network is predicted, and the findings show that neural networks retain the higher susceptibility to noise compared to humans. These findings suggest some useful ideas for adjusting the training strategies in both AI and human learners, signifying the balance between speed, stability, and consistency in learning processes. This research helps a lot to understand the advanced learning dynamics for adaptive learning systems, human-machine collaboration, and performance tuning in both systems.

Keywords: System Dynamics Modelling(SDM), Neural Networks(NN), Human Brain, ARIMA Forecasting.

1 Introduction

In past the 15 years, the interaction between Artificial Intelligence (AI) Learning and Human Learning processes has raised considerable curiosity and popularity [1]. While the AI's machine learning algorithms [2], specifically neural networks [3], are causing revolutionary activity in many domains, understanding the similarity and differences between AI learning and human learning remains a critical area of research. The ability to analyze and model learning dynamics between both systems provides valuable information into their optimization and potential applications in fields ranging from cognitive psychology to real time systems [4].

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Inspired by the human brain, neural networks implement redundant procedures in order to achieve a change of weights and bias so as to learn from a specific data set[5]. Nonetheless, they are confined mostly by architecture design and are incredibly delicate to hyperparameters like learning rate and decay factors, unlike human learning which is influenced by biology and cognition [6]. In addition, realistic and stochastic function of actual neural networks may precipitate factor referred to as noise in the learning process, which makes their behavior more unpredictable [7]. Similarly, those parameters in AI are built-in while contextual effects, biases, and world impacts that are innate born alter the human learning, slow, and far more controllable. These factors might demonstrate certain effect on the learning process tempo, as well as the stability of its further development [8].

This paper's aim is to develop a System Dynamics Model (SDM) in an effort to mimic the learning process of both System; human and a neural network learner. To include more of the important variability in both systems, the model incorporates random noise to, for example, learning rates and decay factors. The patterns of learning behavior of both systems are also explored in this study and the relationships between them characterized using statistical and forecasting tools by comparing the accuracy profiles over time [10]. This is done with a view to improving on the knowledge of the basic rudimentary components that exist within the learning architecture of a system, artificial or human. The information accrued in this research help to design better AI learning paradigms principles and a spectrum of orders to fine tune procedures and strategies of learning for humans in adverse environments [22][11]. Systems, the model samples random noise to certain critical factors such as learning rates and decay factors. This research proposal aims to analyze learning behaviors of both systems, look at their interactions and qualitatively and quantitatively describe them by evaluating accuracy over time forecasts with statistical and forecasting techniques.

The objective of this approach is to better comprehend the basic underlying mechanisms that underpin learning in both artificial and human systems. The results of this research help the creation of AI learning algorithms that are more effective and also offer variety of orders on how to enhance human learning procedures and strategies in challenging settings [11]. The model understanding may enable flexibility and adaptivity in future learning systems; this may also open up new directions in the multidimensional collaborative applications of cognitive science, education and human-computer learning [12]. As pointing out the difference of the approach to apply system dynamics and statistical method, it also provides some glimpse of how huge is the difference of neural network learning compared to humans learning [13]. However, the lack of a significant difference may be due to the simplicity of the simulation, and more complex simulations with real-world data may yield different results. These findings suggest that, within the scope of this simulation, both systems perform similarly in terms of decision accuracy.

2 Literature Survey

Artificial intelligence learning or human learning has been a subject of intervention of study in numerous disciplines such as cognitive science, learning, and machine learning. The rationale for the comparison of learning dynamics of artificial systems and human learners is to acquire some insight about the optimization of the artificial learning models as well as the human learning processes.

Neural networks have come to the level of a rudimentary learning instrument in deep learning as well as machine learning, mimicking the learning mechanisms in a human brain. But the learning processes and methods of AI's ANNs and human's brains are very difference, education, and machine learning. The motivation behind comparing of learning dynamics of artificial systems and human learners is to gain some in-depth knowledge into optimizing both artificial learning models and human learning processes.

Neural networks have become a basic learning tool in deep learning and machine learning, imitating the learning processes of the brain in human. However, the learning processes and methods of AI's neural networks (ANNs) and human brains differ significantly. Parameter estimation in ANNs uses optimization algorithms that can change weights with reference to data; learning rate, bias and decay for minimizing on error. Works prove that overfitting, learning rate scheduling and decay mechanisms have a significant influence on the effectiveness and accuracy of neural networks[5]. For instance, rate at which the rate of weights decay is used to prevent overfitting while, bumps, random noise and fluctuations in the learning rate mimic the stochastic characteristics of environment[6].

However, the difficulties that persist in tackling stochastic noise and other random fluctuations together with the consequent set of fluctuating environments – all of which is crucial in the case of real time – are still unsolved problems within the neural network community. This uncertainty in the design environment can produce models that can be sensitive to slight differences in the initial conditions and hyperparameters[7].These effects can be minimized by using some variability such as stochastic gradient descent (SGD) so that the model is freed from local optimization to achieve better performance[8] systems and human learners can gain some in-depth knowledge into optimizing both artificial learning models and human learning processes.

Neural networks have become a basic learning tool in deep learning and machine learning, imitating the learning processes of the brain in human. However, the learning processes and methods of AI's neural networks (ANNs) and human brains differ significantly. ANNs are trained with optimization algorithms that can adjust weights based on input data, using learning rates, biases, and decay to minimize error. Studies show that overfitting, learning rate scheduling, and decay mechanisms significantly impact the efficiency and accuracy of neural networks[5]. In particular, rate of decay rate of weights plays an important role in avoiding overfitting, and complex variations, for

example random noise and learning rate fluctuations often simulate the inherent unpredictability nature of real-world environment[6].

Despite the advancements in neural networks, the challenges in handling stochastic noise and random variations, especially in real-time applications remains an area of ongoing research. These uncertainty in design environment can lead to models that can be sensitive to minor variations in initial conditions and hyperparameters[7]. Using techniques like stochastic gradient descent (SGD) can reduce these effects by introducing some randomness in the learning process, making the model free from local minima and achieve better performance[8].

Finally, while human learning can be attributed to cerebral and neuron it is a much more enriched process than in the computational artificial neural network and involves learning factors such as memory processing – attention to the world and /or the emotional state that facilitate the learning process [9]. The complexity of learning process is defined by a few internal cognitive processes and a few external processes in the environment surrounding a human so learning is always unpredictable. While neural learning is normally confined to a given algorithm, human learning corresponds to different stimulus types and experiences. Such a type of learning rate variability depending on stress, fatigue and other factors has been discussed in cognitive psychology and [10].

One major area of study in HL is forgetting, where learned content is eroded if it is not refreshed after some time of learning. The human brain shows a trend of forgetting curve and this trend has been used by cognitive scientists to estimate memory retention over time[11]. These models generally rely on predicting the decay of memory where common exponential decay functions capture this process and are directly analogous to the behavior in training a neural network. It is also worth knowing that human learning processes are very frequently non-linear and contain phases of high and low attention, emotions or motivation[12] – thus, the variability inserted in learning trajectories is somehow similar to the randomness introduced in artificial systems. The first one that comes to mind is, Human psychological aspect always varies from one human being to the other while, AI does not have any psychology in it.

A number of papers have discussed the analogy between artificial neural networks and human learn, have discussed how models may be designed to emulate or augment human cognition. Some of the scholars have applied reinforcement learning (RL) to the modeling of human decisions and the algorithms are to learn in the environment through interaction[13]. These approaches are normally based on behavioral psychology and seek to mimic how individuals learn from Award and punishment.

In the context of system dynamics some studies have endeavored to utilize System Dynamics Models (SDM) in modeling learning systems, which also includes intelligent and manual learning systems. Another is the System Dynamic Model or SDM, which is a methodology in modeling and organizing causative relations and feedbacks, stocks and flows that will make a system comprehensible[14]. Most commonly, SDMs have

been used for different types of systems, for example organizational behavior systems[15] and ecological systems[16] However, recently SDMs have been used to model the system in which topography learns comparing with artificial systems[17].

Further, in understanding the interaction between man and the computer, or AI systems, the human computer interaction (HCI) has also held research in how Man along with AI can learn in the same environment. Research in this area examines the creation of new learning technologies on which learners and faculty can provide feedback, as well as which use AI and machine learning to optimize learners' experiences[18]. These papers often demand an explanation for non-stationarity in the form of human variability which includes things such as cognitive workload, mood, and task difficulty.

In the case of artificial learning systems, as with the human mind, randomness is a key to capturing the uncertainty of the environment. The other factors like adding noise and varying learning rates applies stochastic aspect in artificial systems, as it is hard to predict the performance of a system more especially in the real-world problems where there is fluctuations in environmental conditions for noisy data [19].

Similarly human learning contains inherent randomness because of the mental factors, fluctuation in attention and some disturbances. The current works have pointed out that, if these stochastic components are incorporated into models of human learning, then they can better predict the kind of learning curves. The time-series analysis techniques like the ARIMA models have also been used to model time series precedence of learning over time in both machines and humans[21]. Applying ARIMA, the trends of learning in Neural Networks and the human system are modelled to test out accuracy and efficiency in the future based on past records. This makes future researches in this area easier.

These models have been used in practical modeling in different areas including financial modeling, weather prediction and even testing models for students[22]. When applied to learning dynamics, ARIMA models can provide relevant information about the tendencies and potential further behavior of the artificial and, thus, human learning systems which can be useful to tailor the learning paradigm in highly nontrivial settings.

3 Methodology

The entire research work was implemented and evaluated using R programming in R Studio[23], including the architecture diagram using the 'DiagrammeR' package. And packages like 'deSolve', 'ggplot2', 'dplyr', 'corr' are used for visualization and statistical testing and neat alignment of data. The steps are explained as in Fig.1. Simulations were carried out using SDM method. The methodology followed here can be used for other simulation models like ABS or MCS.

3.1 Input Data Collection

Gathering data related to human learning, neural network (NN) learning, and factors influencing noise. Such as task complexity, overfitting in Neural Networks [24], motivation levels in humans, and noise effects.

3.2 Preprocessing

Cleaning and preparing the raw data for modeling. Noise reduction to handle variability in human and NN data. Standardization or normalization for consistent comparisons [25].

3.3 Model Building

Developing mathematical and computational models to simulate learning dynamics like incorporating learning rates, decay rates, and stochastic noise [26]. Building equations and simulations to describe the evolution of human and NN learning accuracy over time.

3.4 Simulation and Analysis

Running dynamic simulations with parameters to study the behavior of both systems under various conditions. Time-series data on accuracy trends [27] provides statistical findings into system behavior.

3.5 Results and Evaluation

Evaluating the simulated data to extract meaningful trends and significant findings such as lag effects or delayed impacts of specific factors [28].

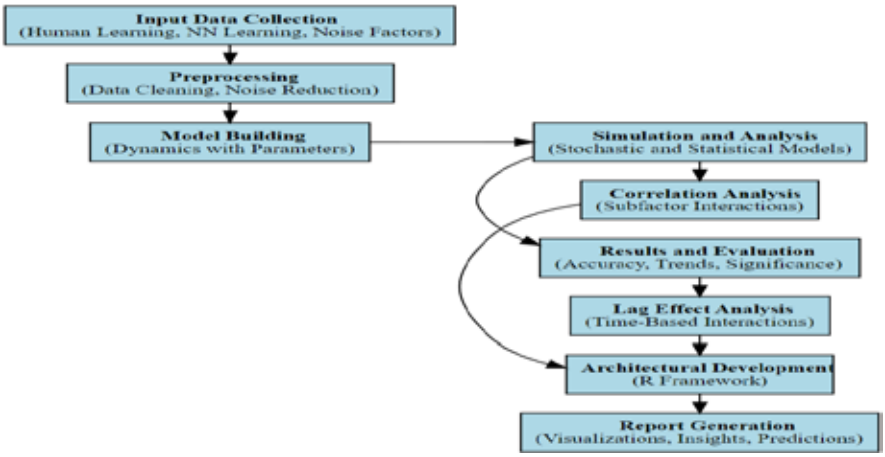

Fig. 1. Architecture diagram of proposed methodology for SDM simulation using R

3.6 Correlation Analysis

By, exploring interactions between subfactors examples include motivation, task complexity, noise etc. And using to determine correlation coefficients to identify relationships either positive or negative[29].

3.7 Lag Effect Analysis

By, investigating time-based dependencies and how learning accuracy evolves with lagged influences. By, considering factors such as delayed human response due to task complexity, gradual NN overfitting effects[30].

3.8 Architectural Development

Then the designing and refining the computational framework for analysis using R has been made[31]. Steps such as creating layered architectures for input, preprocessing, modeling, and visualization.

3.9 Report Generation

Finally producing comprehensive outputs, including visualizations, insights, and predictions for easy understanding.

3.10 Deliverables

Graphs for accuracy trends and summary reports for correlation and lag effects analysis. This forecasts the future performance of both the system.

4 Discussion

The main reason for this study is to explore the dynamics of learning in both artificial neural networks (ANNs) and human learners, using a system dynamics model (SDM)[32] that integrates the influences of random variations and decay. By simulating both artificial and human learning processes, this research aims to fix the gap between AI and human cognitive learning systems, providing insights into their similarities, differences, and potential areas for improvement in each domain[33]. The following discussion will cover the findings, limitations, and implications of this study.

4.1 Key Findings

Through the simulation process that was carried out in R programming, lot of comparative analysis between both the AI's Neural Network and Human Learning. Which is discussed as follows.

Stochastic Dynamics in Both Systems. One of the key findings of this research is the significant role that stochasticity plays in both artificial and human learning Fig.2. In artificial neural networks, introducing random noise and variability in learning rates and decay rates allows the model to better mimic the unpredictable nature of real-world environments.

This randomization prevents overfitting and allows the model to adapt to varying data patterns. Similarly, in human learning, cognitive factors such as attention, motivation, and emotional state introduce inherent randomness into learning processes. The incorporation of stochastic elements in both systems.

Whether it be random noise or fluctuations in learning efficiency, it appears to be critical for accurately simulating real-world learning behavior, where outcomes are rarely deterministic[34].

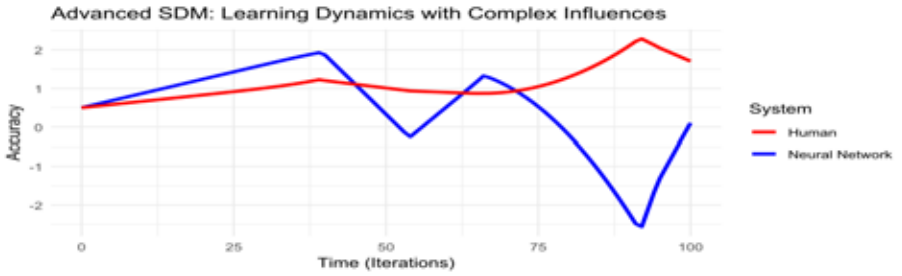

Fig. 2. SDM simulation of Learning in Human vs Neural Network in Complex environment

Decay and Forgetting. Both the artificial neural networks and human learners in this model exhibit decay over time. In the case of ANNs, the decay represents a tendency for the model to "forget" previously learned information if it is not reinforced, which is analogous to the forgetting curve in human memory[35]. The research highlights the similarities between the two systems in their vulnerability to forgetting and suggests that the strategies used to combat overfitting in machine learning—such as regularization, dropout, and reinforcement learning—might find analogs in human learning strategies like spaced repetition and retrieval practice. The model's use of decay rates for both systems underscores the importance of reinforcement in both artificial and human learning, emphasizing that continual learning and reinforcement are necessary to maintain high performance over time.

Human vs Artificial Learning Efficiency. The simulation suggests that while both systems improve over time, the rate of improvement in neural networks (NN_Accuracy) tends to plateau more quickly compared to humans (Human_Accuracy). This observation is consistent with findings in cognitive science Fig.3, where human learning is often non-linear and affected by various psychological, emotional, and contextual factors that can influence the pace of learning.

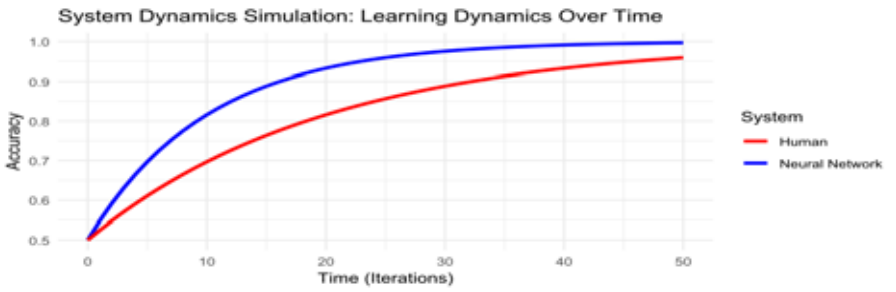

Fig. 3. SDM simulation of Learning in Human vs Neural Network over period of time

Humans, for example, can exhibit sudden leaps in understanding or fall into periods of stagnation due to external influences such as stress, fatigue, or motivation. In contrast, artificial learning tends to follow a more predictable and smoother curve, especially in simpler models without complex emotional or motivational inputs.

Comparison of Forecasted Accuracy Trends. The forecasting analysis using ARIMA models[36] for both systems suggests that while future performance trends for neural networks tend to be stable, human performance exhibits greater variability. This aligns with cognitive theories that emphasize the complexity and variability of human performance over time. Factors such as mental fatigue, stress, and external distractions can cause significant fluctuations in human learning trajectories[37], which are not as easily modeled in typical artificial intelligence systems.

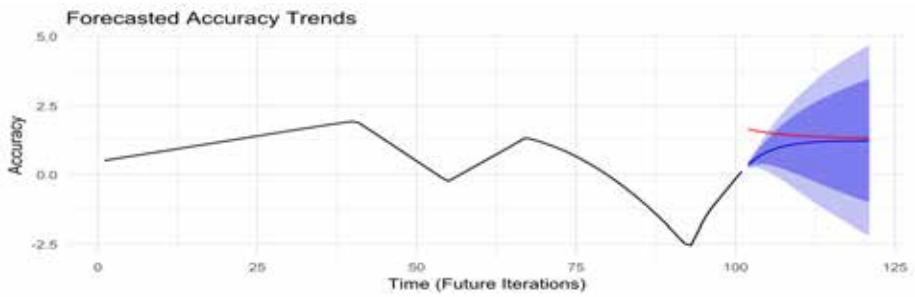

Fig. 4. ARIMA forecasting for Human vs Neural Network performance trends in future

The ARIMA forecasting approach provides a useful statistical tool for predicting future learning trends in both systems and can be extended to account for more complex Fig.4, real-world scenarios involving variable environmental factors.

Significance of Time-Series Analysis. Time series analysis of the accuracy trends over time has revealed value for the long-term dynamics of both artificial and human learning. ARIMA models are applied onto both the systems to forecast their future learning outcomes, enabling the contextualization of its factors (e.g., decay rates, randomnoise) that affect the learning performance with time. Emotional and cognitive variability in human learning systems is further emphasized by the fact that human learning displayed more variability in its predicted trends.[38]

4.2 Implications of these Findings

The findings explain a lot about how both the system work in real time as well as the factors that is influencing it. The main effects in both (System and Time) along with their interaction (System : Time) significantly influence the outcome. The interaction

effect is particularly strong, indicating a complex relationship between System and Time.

Modeling Real-World Learning Systems. This study shows the importance of incorporating stochastic elements in models of both artificial and human learning Fig.5. Random noise introduced in learning rates and decay mechanisms reduces the dependence of simulation on assumptions, and needs to be introduced to give more accurate simulations of learning behavior when the environment is unpredictable. This approach paves the way for building more robust AI system models that are healthy to noise in real world. Findings indicate that learning models should capture cognitive variability and external effects of stress, motivation and attention in human learning contexts.

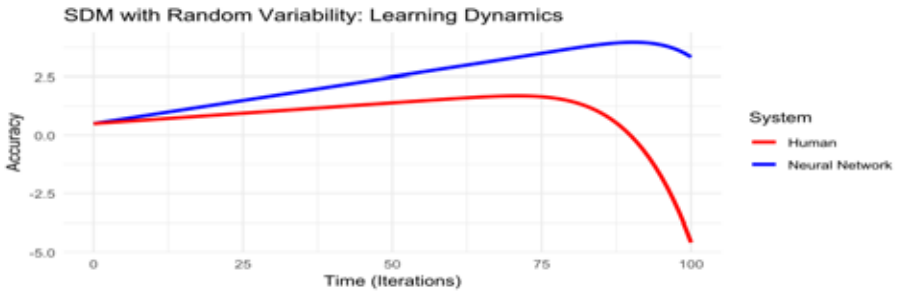

Fig. 5. SDM simulation of Learning in Human vs Neural Network with influence of random external factors

Enhancing Human-AI Collaboration. It also has implications for human-AI collaboration[39]. By understanding the dynamics of both learning systems, artificial and human, perhaps we can learn how these systems can be optimized to work together[40]. For instance, another would be to construct AI systems that become trained on human learning rates proceeding from factors such as emotional state or cognitive load. By contrast, human learners could benefit from AI systems that mimic uncertain real-world environments, enabling positive spillovers to their adaptability and ability to cope with learning difficulties. In educational and professional communities more personalized and more effective learning environments should result.

4.3 Optimization of Learning Models

This is one of the studies were the artificial neural network and human learning models might both benefit from an optimization technique that incorporates some of the derived insights. Models can become more resilient for AI if we improve the balance between decay rate and learning rate learning, and introduce adaptive learning mechanisms that take account of external noise or disruptions. Our insights from the study could also inform new learning strategies aimed at maintaining motivation and focus, for example

through dynamic learning schedules that adjust in real time to emotional states or cognitive load [41] in order to better enable long term learning outcomes.

4.4 Limitations of the Study

While the model offers valuable insights into learning dynamics, several limitations should be acknowledged

Simplified Assumptions. The model simplifies both human and artificial learning dynamics by using basic decay functions and random noise. Real-world learning is far more complex and involves a wider range of psychological, social, and environmental factors[42] that are not captured in this model.

Lack of Contextual Factors in Human Learning. The model does not incorporate the wide variety of contextual factors that influence human learning, such as cultural differences, social interactions, or individual differences in cognition.

Over-Simplification of AI Learning. The model uses a relatively simple approach to simulate neural network behavior. In practice, artificial neural networks often involve complex architectures and advanced techniques such as backpropagation[43], batch normalization, and adaptive learning rates could influence the dynamics observed in this research.

5 Results

This section provides a statistical analysis of the results from the model simulation, including the ANOVA summary and t-test results, to examine the dynamics of neural network and human accuracy over time.

5.1 ANOVA Results

The results from the analysis of variance (ANOVA)[44] provide insights into the significance of the system type (Neural Network vs Human Brain), time, and their interaction effects on the accuracy values Fig.6.

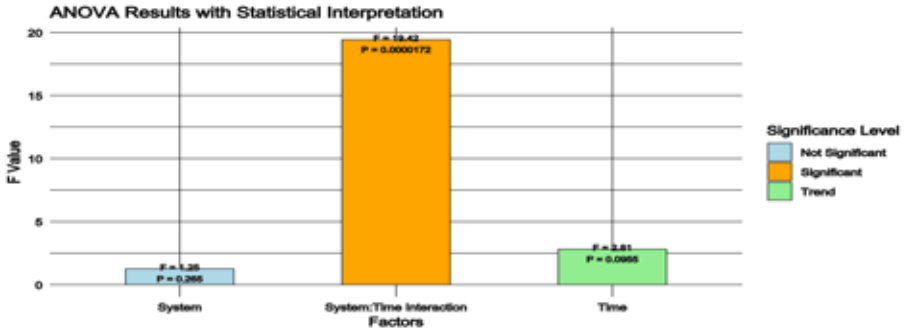

Fig. 6. ANOVA result of learning in Human vs Neural Network with System and Time Interaction

System (Main Effect). The F score at 1,198 is 1.248 and the p-value = 0.2653 ($p<0.05$) shows the main effect of the system (Neural Network vs Human) is not statistically significant. This indicates that, on average, there is no significant difference between the accuracy of the neural network and human systems when considered independently of time.

Time (Main Effect). The F score at 1,198 is 2.807 and the p-value = 0.0955($p<0.05$) shows the main effect of time is also not highly significant at the conventional 0.05 level. However, the p-value is just below 0.1, which suggests a potential trend indicating that accuracy may change over time, but the evidence is not strong enough to declare a statistically significant change across time in both systems.

System and Time (Interaction Effect). The F score at 1,198 is 19.422 and the p-value = 0.0000172 shows the interaction effect between system type and time line is highly significant. This suggests that the way the accuracy of the neural network and human systems changes over time is different. The neural network and human systems have differing learning curves, and their behaviors over time are not parallel. Specifically, this interaction indicates that the accuracy of both systems evolves differently as time progresses, with one system possibly improving faster or more consistently over the other.

Residuals. The residuals represent unexplained variability, with a sum of squares of 37.90 score and a mean square of 0.191 score. The residual variability is a crucial factor to consider when assessing the overall fit of the model. While there is some unexplained variation, the significant interaction effect indicates that much of the variation in accuracy can be attributed to differences in system type and the time evolution of those systems.

5.2 T-Test Results

The Welch Two-Sample t-test[45] was involved here to compare the accuracy of the neural network and human systems at the final time point Fig.7. This test evaluates whether the difference in accuracy means between the two systems is statistically significant.

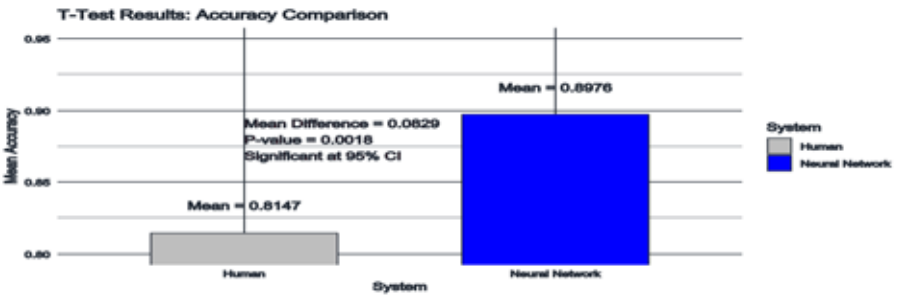

Fig. 7. T-Test showing accuracy and learning differences in Human vs Neural Network

Test Statistic (t). The t-statistic value of 3.2082 shows that there is a substantial difference between the two groups.

Degrees of Freedom (df). The degrees of freedom for this t-test are 99.992, which suggests that the comparison was made with a nearly normal distribution.

P-value. The p-value = 0.0018, which is less than 0.05, indicating that the difference between the mean accuracies of the neural network and human systems is statistically significant. Specifically, the neural network shows higher accuracy (mean = 0.8976) compared to the human system (mean = 0.8147). Although the difference is only 0.0829.

Confidence Interval. For the difference in means is [0.0316, 0.1342], which does not contain zero, further confirming that the difference in accuracy between the two systems is statistically significant at Confidence Interval (95%).

5.3 Pearson Correlation

The correlation matrix[46] provides insights into the relationships between subfactors influencing human and neural network learning. Below is an analysis of the significant correlations observed.

Overfitting_NN. Correlation with Human_Accuracy of 0.148 shows a weak positive relationship. As overfitting increases, human accuracy shows a slight upward trend, likely due to differing dynamics in task complexity handling between humans and neural networks. Correlation with Task_Complexity of 0.0826 shows a very weak positive association, suggesting that as task complexity increases, overfitting has a marginally higher impact.

NN_Accuracy. Correlation with Noise_Impact_NN of -0.129 this weak negative correlation suggests that stochastic noise affecting neural networks reduces their accuracy slightly. Correlation with Human_Accuracy of -0.158 indicates a weak negative relationship indicates potential competition or differing learning trajectories between humans and neural networks.

Noise_Impact_NN. Correlation with Motivation_Human of -0.230 this moderate negative relationship indicates that as noise impacts neural networks, human motivation may decrease, potentially reflecting challenges in collaborative tasks. Correlation with Task_Complexity of -0.0764 shows a very weak negative correlation implies minimal impact of noise on task complexity.

Human_Accuracy. Correlation with Task_Complexity of 0.116 shows a weak positive correlation suggests that humans perform slightly better as task complexity increases, likely due to adaptive problem-solving skills. Correlation with Noise_Impact_Human of 0.117 shows a weak negative correlation highlights the detrimental effect of noise on human accuracy.

Task_Complexity. Correlation with Motivation_Human of 0.153 shows a weak positive relationship suggests that increased task complexity may enhance human motivation, possibly due to the challenge presented.

Motivation_Human. Correlation with Noise_Impact_Human of 0.188 shows a weak positive correlation indicates that human motivation slightly increases with noise, which might represent a stress-induced drive to improve performance.

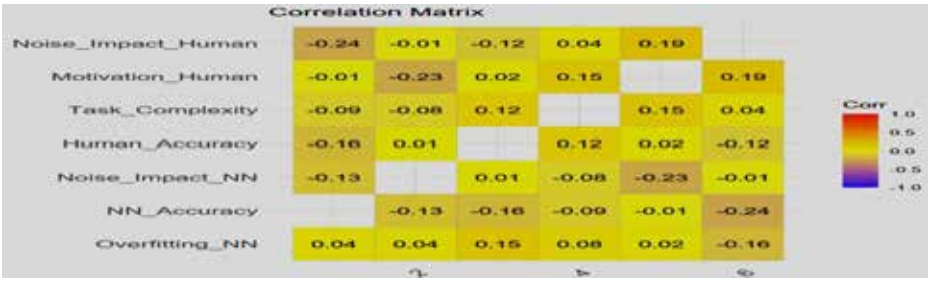

Fig. 8. Correlation test involving sub-factors of both Human and Neural Network

These correlation results Fig.8 suggest that, while both systems improve their accuracy over time, the neural network performs better overall. This outcome might be due of the deterministic nature of the neural network's[47] learning algorithm, which allows it to consistently optimize its performance, unlike human learning, which is subject to fluctuations and external factors.

6 Conclusion

The ANOVA results highlight that there is a more than enough interaction between type of system and time[48], indicating that the learning behaviors of the neural network and human systems diverge over time. While the systems start with similar accuracy levels, their trajectories of improvement differ, likely due to the distinct nature of their learning processes.

It also shows that the neural network performs better than humans in accuracy at the final time point, however, this is a small difference. Higher performance of the neural network can be related to their ability to learn more structured and consistently than the human learners due to the psychological and environmental factors. Here we find that the neural network provides a more predictable and consistent learning process, while human learners show more variability in their learning curve work's higher performance can be attributed to its ability to learn in a more structured and consistent manner compared to human learners, who may experience varying levels of effectiveness due to psychological and environmental factors.

These findings suggest that while the neural network provides a more predictable and consistent learning process, human learners exhibit more variability in their learning curves. This variability is driven by the stochastic nature of human learning, in which attention, motivation and memory play a role. Although human learning is slow, over time one becomes more accurate with emotional understanding, determination and life experience. AI learning is accurate if time is the very important factor and if the subjects involved are very complex.

7 Future Research

Such work could be carried out in another study where the above parameters; the learning rate, decay rate and random noise, are varied and the long-term behavior of both systems analyzed. With these parameters one can just further stress on how such systems would work in other learning situations still leaving the whole exercise to the users.

Preliminary testing of the models may be done through the use of cognitive theories of learning such as spaced repetition model, or dual process theory to establish how the

models could better be incorporated so as to mimic the real-world environment and dynamics of human learning.

Further, it would be interesting to extend this simulation to cover other types of learning, for example deep learning architectures, and compare performance of the model under such circumstances with performance of a human subject under conditions which may include multitasking, emotions, or stress.

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