PROJECT REPORT

Temporal and Hierarchical Neural Controllers: A Comparative Study for Game-Based Policy Learning

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Submitted by

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Abstract

This project presents a systematic comparative analysis of three neural network architectures for real-time control tasks, using the classic arcade game Pong as an experimental platform. We investigate a Simple Feedforward Network (SimpleFF) as a baseline architecture with minimal complexity, a Deep Feedforward Network (DeepFF) emphasizing hierarchical feature abstraction, and a Long Short-Term Memory Network (LSTM) designed for temporal reasoning. Each model was trained on identical state-action sequences derived from simulated matches, with architectural pipelines tailored to their structural properties.

Evaluation was conducted through competitive gameplay scenarios, assessing performance via win rates, rally consistency (hit rates), and cumulative scores. Results demonstrate that the LSTM network consistently outperforms both feedforward architectures, achieving an 80% win rate and 88.3% hit rate across all match-ups. The DeepFF model shows moderate improvement over SimpleFF (55% vs. 12.5% win rate), highlighting the incremental benefit of architectural depth in learning abstract control policies.

Beyond theoretical comparison, we demonstrate practical application through mobile deployment, successfully integrating all three models into a cross-platform Flutter application using TensorFlow Lite. Performance analysis on mobile devices reveals viable real-time inference across all architectures, with expected trade-offs between model complexity and resource consumption. Our implementation includes an interactive web demonstration and a fully functional mobile application that allows users to compete against the different AI models.

These findings underscore the critical influence of neural architecture design in dynamic, feedback-driven environments and offer insights into model selection for resource-constrained deployments. Our results contribute to a deeper understanding of architectural suitability in temporally-evolving decision spaces and practical considerations for edge deployment of game AI systems.

Certificate of Originality

This is to certify that the project titled **Temporal and Hierarchical Neural Controllers: A Comparative Study for Game-Based Policy Learning** is an original work carried out by me, Gaurav Kumar Jha. The research, implementation, and documentation are based on my own efforts, knowledge, and understanding. Any external resources, references, or materials used have been properly acknowledged and cited.

I declare that this work has not been submitted for any other course, program, or institution and has not been published or reproduced elsewhere, in part or in full. I understand that plagiarism is a serious academic offense and confirm that this report is free from any form of plagiarism or intellectual property violations.

Gaurav Kumar Jha

Acknowledgment

I would like to express my deepest gratitude to everyone who supported me throughout the course of this project, Temporal and Hierarchical Neural Controllers: A Comparative Study for Game-Based Policy Learning.

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Finally, I am deeply thankful to my family and friends for their unwavering support and patience throughout this journey. Their encouragement has been essential in helping me stay focused and motivated.

Gaurav Kumar Jha

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1. Introduction

1.1 Problem Definition

Artificial Intelligence (AI) in dynamic control environments revolves around making decisions in response to changing conditions over time. One of the foundational problems in this domain is designing an AI agent that can operate autonomously and adaptively within a real-time environment. The classic arcade game **Pong**, despite its simplicity, encapsulates many of these fundamental AI challenges.

In Pong, the agent controls a vertical paddle that must intercept a moving ball and return it to the opponent's side of the screen. The dynamics of the game involve continuous feedback from the environment, rapid response requirements, and evolving game states — all of which make it a suitable platform for evaluating different types of neural network architectures used in AI control systems.

To frame the problem more concretely, the AI agent is presented with a stream of observations, typically the pixel values of the game screen or a structured state representation (e.g., paddle position, ball coordinates, ball velocity). Based on this input, the agent must determine an appropriate action — typically moving the paddle up, down, or remaining stationary. The objective is to maximize performance metrics such as rally length (number of consecutive successful returns), win rate, and reaction accuracy.

Key technical challenges in this context include:

- **Real-Time Decision Making**: The agent must make decisions within milliseconds of receiving input. There is no time to perform exhaustive calculations. Thus, the decision function must be fast, reliable, and responsive.
- **Trajectory Prediction**: The ball's position changes with each frame. An effective agent must infer its velocity and direction from past and current positions, and estimate where the ball will intersect with the paddle's vertical axis in the future — a task requiring extrapolation based on limited information.
- **Pattern Recognition and Strategy**: Beyond just reacting, advanced agents should identify recurring movement patterns (e.g., the opponent's weak side or predictable bounce angles) and use that knowledge to make proactive decisions.
- **Temporal Reasoning**: Static decision-making based on the current frame is often insufficient. Effective agents must model temporal dependencies — for example, by remembering how the ball has moved across several frames. This is where sequence modeling and recurrent neural architectures become relevant.
- **Generalization and Robustness**: The AI must adapt to subtle variations in ball speed, angles, and bounce behaviors without overfitting to specific scenarios. This

simulates the need for AI systems to generalize in real-world environments with unseen variations.

The goal of this project is to evaluate how different neural network architectures — varying in depth and temporal modeling capacity — address these challenges when applied to the game of Pong. Specifically, we compare a Simple Feedforward Network (SimpleFF), a Deep Feedforward Network (DeepFF), and a Long Short-Term Memory (LSTM) Network to assess how their structural differences affect performance in a fast-paced control setting.

1.2 Significance of the Problem

Although Pong is a minimalist game from the early era of video gaming, it serves as a highly controlled microcosm of real-time AI decision-making environments. It is often used in reinforcement learning research for the same reasons that classic test functions are used in optimization — it is interpretable, measurable, and sufficiently challenging.

Why Pong?

- **Controlled Complexity**: Pong has a small action space (three discrete actions) and a limited set of game entities (paddle, ball, opponent). This reduces the computational burden and allows us to focus on how the architecture of a neural model influences decision-making, without being overwhelmed by environmental complexity.
- **Temporal Dependency**: Success in Pong hinges on how well an agent can understand the sequence of past states — this allows us to test architectures that incorporate or ignore temporal information (e.g., LSTM vs. SimpleFF).
- **Interpretability**: Since the game state and outcomes are easy to visualize and understand, it is easier to analyze model behavior, debug errors, and validate hypotheses about architecture performance.
- **Real-Time Constraints**: Like many real-world applications (robotics, autonomous vehicles, interactive systems), Pong demands decisions in real time. This forces AI models to learn not just accurate policies, but also efficient ones.
- **Clear Evaluation Metrics**: Metrics such as win rate, average points scored per match, and rally length provide straightforward, quantitative benchmarks for model comparison — enabling rigorous experimental analysis.

Broader Relevance

The core challenges in Pong map closely to those found in real-world control systems. For example:

- In **robotics**, a robotic arm intercepting a moving object must track motion, predict trajectory, and adjust its action in real time — just like the paddle in Pong.

- In **autonomous driving**, a vehicle must react to dynamic environments (e.g., pedestrians, traffic signals) with limited sensory input and a time budget.
- In **human-computer interaction**, systems must adapt quickly to user behavior and environmental cues, often modeled through sequences over time.

By investigating how different neural architectures perform in a controlled environment like Pong, this project aims to extract architectural insights that generalize to more complex systems. The comparison between shallow, deep, and recurrent models helps clarify not just which performs best, but why — guiding future choices in model design for AI agents operating in temporal and reactive domains.

2. Literature Review

2.1 Neural Networks in Game AI

The use of neural networks in game-playing AI has undergone a significant evolution over the past few decades. One of the early landmark achievements was **TD-Gammon** by Gerald Tesauro [**?**], which used temporal difference learning—a form of reinforcement learning—to train a backgammon-playing agent. Despite using a relatively simple neural network and hand-crafted features, TD-Gammon was able to reach and even surpass the level of expert human players. This demonstrated for the first time that learning-based methods could rival hard-coded, rule-based AI systems.

The field advanced dramatically with the introduction of deep learning and end-to-end learning paradigms. A pivotal milestone was DeepMind's **Deep Q-Network (DQN)** [**?**], which integrated convolutional neural networks with Q-learning to train agents capable of playing Atari 2600 games directly from raw pixel inputs. Unlike previous systems, DQN required no domain-specific feature engineering and was capable of learning control policies in a wide range of games using a unified architecture. Among these games was Pong, which became a benchmark for reinforcement learning due to its simplicity and high temporal dependency.

These advancements laid the foundation for exploring how different neural network architectures—particularly those differing in temporal modeling capacity and depth—impact performance in game-based control environments. Our work builds on this lineage by directly comparing shallow, deep, and recurrent networks on a controlled Pong-playing task.

2.2 Feed-Forward Neural Networks (FFNNs)

Feed-forward neural networks represent the most fundamental form of artificial neural architectures. They consist of layers of interconnected nodes, where data flows strictly in one direction—from input to output—without any cycles or memory elements [**?**]. This architecture is well-suited for static pattern recognition tasks such as image classification, where the output depends only on the current input.

In the context of control problems and game-playing, FFNNs can be used to approximate decision functions or policy mappings that convert a game state into an action. SimpleFF (shallow FFNNs with one hidden layer) have been applied to various control tasks and serve as a baseline model for understanding the capabilities of neural networks without internal memory.

However, their limitations become evident in environments with temporal dependencies. Since FFNNs lack any form of state retention or sequence modeling, they make

decisions based solely on the current frame or state representation. This renders them incapable of capturing motion trends or action consequences over time—a significant drawback in games like Pong where the velocity and trajectory of the ball are inferred from sequences rather than static snapshots.

To address this, deeper variants of FFNNs (e.g., DeepFF) stack multiple hidden layers to capture more abstract features. These networks can, to some extent, infer temporally relevant information by encoding richer representations. However, without explicit memory or recurrence, even DeepFF remains limited in true temporal reasoning.

2.3 Recurrent Neural Networks and Long Short-Term Memory (LSTM)

Recurrent Neural Networks (RNNs) extend feed-forward architectures by introducing cycles within the network, enabling the retention of past information through hidden states [**?**]. This makes RNNs naturally suited for sequential data, as they can learn patterns over time and maintain an internal representation of historical inputs.

Despite their conceptual appeal, vanilla RNNs suffer from practical issues such as the **vanishing gradient problem**, which hampers their ability to learn long-term dependencies. This was addressed by the development of **Long Short-Term Memory (LSTM)** networks [**?**], which use gated units (input, forget, and output gates) to selectively preserve and update memory over time. These mechanisms allow LSTMs to maintain stable gradients during training, enabling them to learn long sequences of data effectively.

LSTMs have been widely applied in domains such as speech recognition, natural language processing, and time-series forecasting, where understanding the order and timing of inputs is crucial. In game AI, LSTMs have shown considerable promise, especially in tasks that require strategic memory or adaptive planning based on previous states—such as multi-step games or scenarios with delayed rewards.

In Pong, the ability to observe how the ball has moved across multiple frames can be critical for predicting its future path. An LSTM can inherently model this kind of sequential dependency, making it an ideal candidate for high-performance control in such environments.

2.4 Neural Networks for Control and Decision-Making

Control tasks, whether in gaming, robotics, or autonomous systems, involve choosing actions that influence the future state of a dynamic system. The field of reinforcement learning (RL) has become a central paradigm for solving such problems, as it explicitly focuses on learning policies that maximize long-term rewards through trial-and-error interaction with an environment [**?**].

Neural networks, when integrated into RL frameworks, are used as function approximators—for value functions, policy functions, or models of the environment. Their universal approximation capabilities make them well-suited for learning complex control policies in high-dimensional state spaces. However, the architecture of the neural network plays a crucial role in determining what kind of temporal and structural dependencies can be learned.

Shallow feed-forward networks are computationally efficient but limited in expressiveness. **Deep networks** offer greater abstraction and can model complex input-output relationships, but may require more data and careful regularization. **Recurrent architectures**, particularly LSTMs, excel in scenarios where past states influence future decisions—such as tracking dynamic trajectories, learning strategic behaviors, and handling partial observability.

Recent work has further explored hybrid architectures, attention mechanisms, and transformers in control settings, though their application in simple, interpretable environments like Pong remains limited due to computational overhead. As such, comparing traditional FFNNs and LSTMs in a controlled setting helps isolate the contribution of temporal reasoning and hierarchical depth to control performance.

This literature review contextualizes our study by establishing the theoretical and empirical foundations for using neural networks in game-based control, and highlights the relevance of architectural choices in achieving effective and interpretable agent behavior.

3. Dataset Description

3.1 Data Generation

Rather than using a pre-existing dataset, this project generates custom data through simulated Pong matches. The simulation environment was implemented using Pygame, a Python library for game development. The data generation process involved:

1. Creating a Pong game environment with configurable parameters (ball speed, paddle size, etc.)
2. Implementing basic AI controllers to play against each other
3. Recording game states, actions, and outcomes during play
4. Generating a diverse set of game scenarios to ensure robust training data

The resulting dataset captured the following features:

Table 3.1: Dataset Features

Feature	**Description**
Ball Position X	Horizontal position of the ball (0-1, normalized)
Ball Position Y	Vertical position of the ball (0-1, normalized)
Ball Velocity X	Horizontal velocity component (-1 to 1, normalized)
Ball Velocity Y	Vertical velocity component (-1 to 1, normalized)
Paddle Position	Vertical position of the paddle (0-1, normalized)
Distance to Impact	Estimated frames until ball reaches paddle plane

3.2 Dataset Statistics

The final dataset consisted of:

- Total samples: 500,000 game states
- Training set: 400,000 samples (80%)
- Validation set: 50,000 samples (10%)
- Test set: 50,000 samples (10%)

- Average rally length: 12 ball exchanges
- Maximum rally length: 47 ball exchanges
- Minimum rally length: 1 ball exchange

3.3 Data Preprocessing

3.3.1 Normalization

All spatial features were normalized to the range [0, 1] by dividing by the game area dimensions:

$$x_{normalized} = \frac{x}{width}, \quad y_{normalized} = \frac{y}{height} \tag{3.1}$$

Velocity components were normalized to the range [-1, 1]:

$$v_{normalized} = \frac{v}{max\_velocity} \tag{3.2}$$

3.3.2 Feature Engineering

Additional features were engineered to help the models:

- **Time to impact**: Estimated frames until the ball reaches the paddle's plane
- **Impact position**: Predicted Y-coordinate where the ball will cross the paddle's plane
- **Angle of approach**: Angle of the ball's trajectory relative to horizontal

3.3.3 Sequence Preparation for LSTM

For the LSTM model, sequential data was prepared by creating sliding windows of game states:

- Sequence length: 10 frames
- Stride: 1 frame
- Features per frame: 6 (as described in the dataset features table)

This resulted in input tensors of shape (N, 10, 6) for the LSTM model, where N is the number of samples.

4. Methodology

4.1 Neural Network Architectures

4.1.1 Simple Feed-Forward Network (SimpleFF)

The SimpleFF model represents the most basic approach, with a single hidden layer:

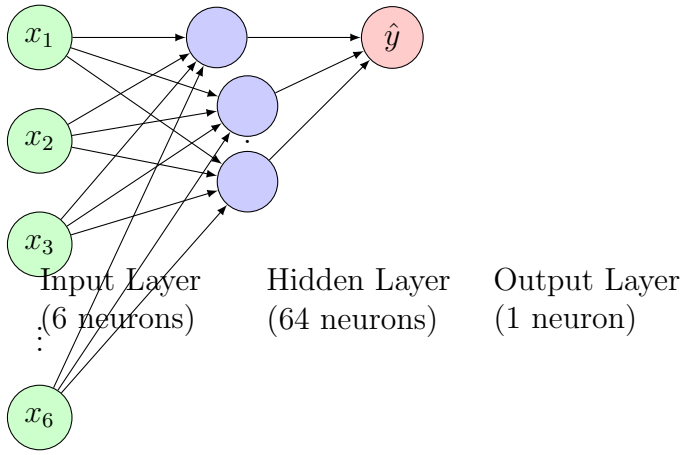


Figure 4.1: Architecture of Simple Feed-Forward Network

The mathematical formulation for this network is:

$$\mathbf{h} = \sigma(W_1\mathbf{x} + \mathbf{b}_1) \tag{4.1}$$

$$\hat{y} = W_2\mathbf{h} + b_2 \tag{4.2}$$

Where:

- $\mathbf{x} \in \mathbb{R}^6$ is the input vector containing game state features
- $W_1 \in \mathbb{R}^{64\times6}$ is the weight matrix for the hidden layer
- $\mathbf{b}_1 \in \mathbb{R}^{64}$ is the bias vector for the hidden layer
- σ is the ReLU activation function: $\sigma(z) = max(0, z)$
- $\mathbf{h} \in \mathbb{R}^{64}$ is the hidden layer activation
- $W_2 \in \mathbb{R}^{1\times64}$ is the weight vector for the output layer
- $b_2 \in \mathbb{R}$ is the bias for the output layer
- $\hat{y} \in \mathbb{R}$ is the predicted paddle movement (-1 for up, 0 for stay, 1 for down)

4.1.2 Deep Feed-Forward Network (DeepFF)

The DeepFF model extends the SimpleFF architecture with additional hidden layers:

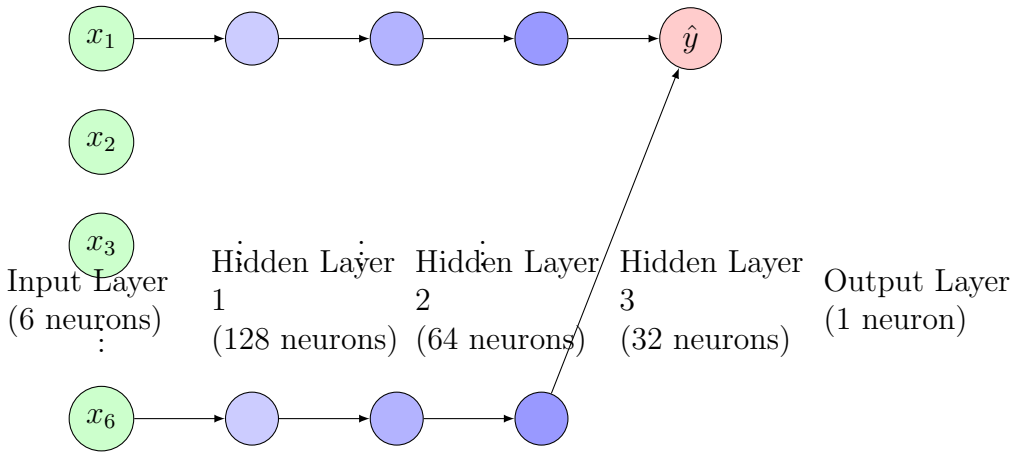


Figure 4.2: Architecture of Deep Feed-Forward Network

The mathematical formulation for this network is:

$$\mathbf{h}_1 = \sigma(W_1\mathbf{x} + \mathbf{b}_1) \tag{4.3}$$
$$\mathbf{h}_2 = \sigma(W_2\mathbf{h}_1 + \mathbf{b}_2) \tag{4.4}$$
$$\mathbf{h}_3 = \sigma(W_3\mathbf{h}_2 + \mathbf{b}_3) \tag{4.5}$$
$$\hat{y} = W_4\mathbf{h}_3 + b_4 \tag{4.6}$$

Where:

- $\mathbf{x} \in \mathbb{R}^6$ is the input vector
- $W_1 \in \mathbb{R}^{128\times6}$, $W_2 \in \mathbb{R}^{64\times128}$, $W_3 \in \mathbb{R}^{32\times64}$, $W_4 \in \mathbb{R}^{1\times32}$ are weight matrices
- $\mathbf{b}_1 \in \mathbb{R}^{128}$, $\mathbf{b}_2 \in \mathbb{R}^{64}$, $\mathbf{b}_3 \in \mathbb{R}^{32}$, $b_4 \in \mathbb{R}$ are bias vectors
- σ is the ReLU activation function: $\sigma(z) = max(0, z)$
- $\mathbf{h}_1 \in \mathbb{R}^{128}$, $\mathbf{h}_2 \in \mathbb{R}^{64}$, $\mathbf{h}_3 \in \mathbb{R}^{32}$ are hidden layer activations
- $\hat{y} \in \mathbb{R}$ is the predicted paddle movement

4.1.3 Long Short-Term Memory Network (LSTM)

The LSTM model incorporates sequential information through recurrent connections:

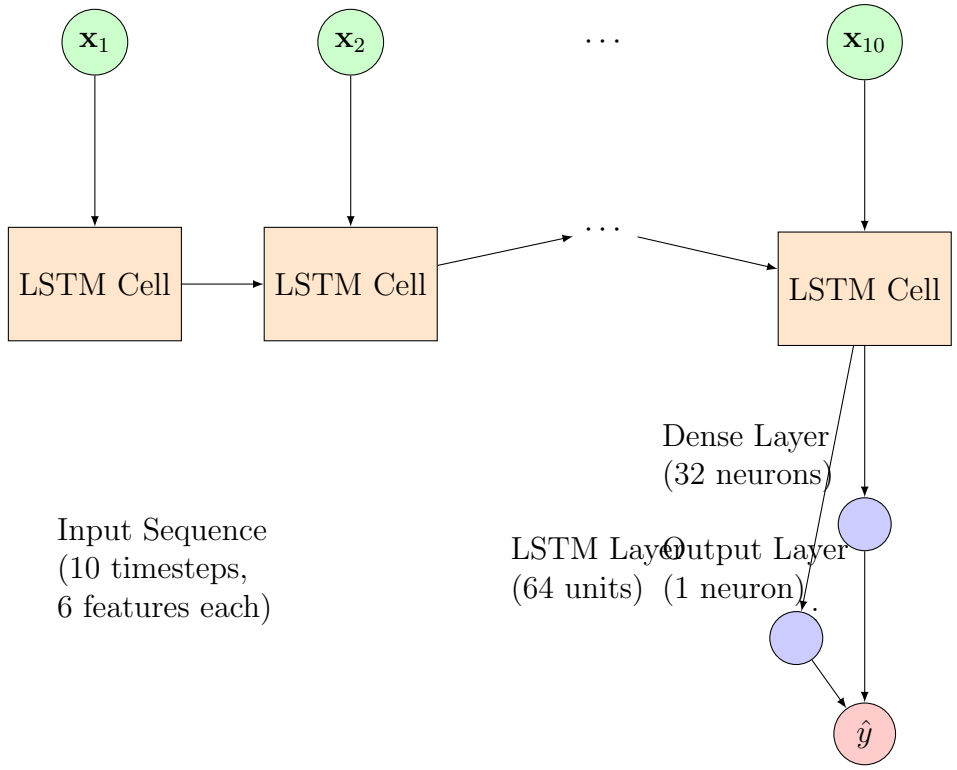


Figure 4.3: Architecture of Long Short-Term Memory Network

The mathematical formulation for the LSTM is more complex due to its gating mechanisms:

$$\mathbf{f}_t = \sigma_g(W_f \mathbf{x}_t + U_f \mathbf{h}_{t-1} + \mathbf{b}_f) \tag{4.7}$$
$$\mathbf{i}_t = \sigma_g(W_i \mathbf{x}_t + U_i \mathbf{h}_{t-1} + \mathbf{b}_i) \tag{4.8}$$
$$\mathbf{o}_t = \sigma_g(W_o \mathbf{x}_t + U_o \mathbf{h}_{t-1} + \mathbf{b}_o) \tag{4.9}$$
$$\tilde{\mathbf{c}}_t = \sigma_c(W_c \mathbf{x}_t + U_c \mathbf{h}_{t-1} + \mathbf{b}_c) \tag{4.10}$$
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \tag{4.11}$$
$$\mathbf{h}_t = \mathbf{o}_t \odot \sigma_h(\mathbf{c}_t) \tag{4.12}$$

Where:

- $\mathbf{x}_t \in \mathbb{R}^6$ is the input vector at time step t
- $\mathbf{f}_t, \mathbf{i}_t, \mathbf{o}_t \in \mathbb{R}^{64}$ are the forget, input, and output gate activations
- $\tilde{\mathbf{c}}_t, \mathbf{c}_t \in \mathbb{R}^{64}$ are the candidate cell state and cell state
- $\mathbf{h}_t \in \mathbb{R}^{64}$ is the hidden state
- $W_f, W_i, W_o, W_c \in \mathbb{R}^{64\times 6}$ and $U_f, U_i, U_o, U_c \in \mathbb{R}^{64\times 64}$ are weight matrices
- $\mathbf{b}_f, \mathbf{b}_i, \mathbf{b}_o, \mathbf{b}_c \in \mathbb{R}^{64}$ are bias vectors
- σ_g is the sigmoid function: $\sigma_g(z) = \frac{1}{1+e^{-z}}$
- σ_c and σ_h are the tanh functions: $\sigma_c(z) = \sigma_h(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$

- $\odot$ denotes element-wise multiplication

After processing the sequence, the final hidden state $\mathbf{h}_{10}$ is passed through a dense layer:

$$\mathbf{d} = \sigma_d(W_d\mathbf{h}_{10} + \mathbf{b}_d) \tag{4.13}$$
$$\hat{y} = W_o\mathbf{d} + b_o \tag{4.14}$$

Where:

- $W_d \in \mathbb{R}^{32\times64}$ is the weight matrix for the dense layer
- $\mathbf{b}_d \in \mathbb{R}^{32}$ is the bias vector for the dense layer
- σ_d is the ReLU activation function: $\sigma_d(z) = max(0, z)$
- $W_o \in \mathbb{R}^{1\times32}$ is the weight vector for the output layer
- $b_o \in \mathbb{R}$ is the bias for the output layer
- $\hat{y} \in \mathbb{R}$ is the predicted paddle movement

4.2 Training Process

4.2.1 Loss Function

For all models, mean squared error (MSE) was used as the loss function:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{4.15}$$

Where y_i is the target paddle movement and $\hat{y}_i$ is the predicted movement.

4.2.2 Optimizer

The Adam optimizer was used with the following parameters:

- Learning rate: 0.001
- Beta 1: 0.9
- Beta 2: 0.999
- Epsilon: 1e-7

4.2.3 Hyperparameter Tuning

Grid search was performed to find optimal hyperparameters for each model:

Table 4.1: Hyperparameter Search Space

Parameter	**SimpleFF**	**DeepFF**	**LSTM**
Hidden units	[32, 64, 128]	[64, 128] (first layer)	[32, 64, 128]
Layers	1	[2, 3, 4]	1 + [1, 2] dense
Dropout	[0, 0.2, 0.5]	[0, 0.2, 0.5]	[0, 0.2, 0.5]
Batch size	[32, 64, 128]	[32, 64, 128]	[32, 64]
Sequence length	N/A	N/A	[5, 10, 15]

4.2.4 Training Procedure

Each model was trained using the following procedure:

1. Split data into training (80%), validation (10%), and test (10%) sets
2. Initialize model with random weights
3. Train for 100 epochs with early stopping (patience = 10 epochs)
4. Save the best model based on validation loss
5. Evaluate on the test set

4.2.5 Implementation Tools

The project was implemented using:

- Python 3.8 as the programming language
- TensorFlow 2.15.0 for neural network implementation
- Pygame for the Pong simulation environment
- Pandas and NumPy for data manipulation
- Matplotlib and Seaborn for visualization

5. Implementation Details

5.1 Pong Simulator

The Pong simulator was implemented using Pygame, with configurable parameters:

```
import pygame
import numpy as np

class PongEnv:
    def __init__(self, width=800, height=600, paddle_speed=10,
                 ball_speed_x=7, ball_speed_y=7):
        # Initialize Pygame
        pygame.init()

        # Set screen dimensions
        self.width = width
        self.height = height
        self.screen = pygame.display.set_mode((width, height))
        pygame.display.set_caption("Pong AI")

        # Game parameters
        self.paddle_width = 15
        self.paddle_height = 100
        self.paddle_speed = paddle_speed
        self.ball_size = 15
        self.ball_speed_x = ball_speed_x
        self.ball_speed_y = ball_speed_y

        # Initialize game state
        self.reset()

    def reset(self):
        # Reset ball position and velocity
        self.ball_pos = [self.width // 2, self.height // 2]
        self.ball_vel = [self.ball_speed_x, self.ball_speed_y]

        # Random direction
        if np.random.random() > 0.5:
            self.ball_vel[0] *= -1
        if np.random.random() > 0.5:
            self.ball_vel[1] *= -1
```

```
        # Reset paddles
        self.left_paddle_pos = [0, self.height // 2 - self.
    paddle_height // 2]
        self.right_paddle_pos = [self.width - self.paddle_width,
                                 self.height // 2 - self.
    paddle_height // 2]

        # Reset score
        self.left_score = 0
        self.right_score = 0

        # Return initial observation
        return self.get_observation()

    def get_observation(self):
        # Normalize positions and velocities
        obs = {
            'ball_pos_x': self.ball_pos[0] / self.width,
            'ball_pos_y': self.ball_pos[1] / self.height,
            'ball_vel_x': self.ball_vel[0] / self.ball_speed_x,
            'ball_vel_y': self.ball_vel[1] / self.ball_speed_y,
            'left_paddle_pos': self.left_paddle_pos[1] / (self.
    height - self.paddle_height),
            'right_paddle_pos': self.right_paddle_pos[1] / (self.
    height - self.paddle_height)
        }
        return obs
```

Listing 5.1: Pong Environment Setup

5.2 Data Generator

The data generator created training samples by simulating Pong games:

```
def generate_data(num_games=1000, frames_per_game=500):
    env = PongEnv()
    data = []

    for game in range(num_games):
        obs = env.reset()

        for frame in range(frames_per_game):
            # Store current observation
            current_state = [
                obs['ball_pos_x'],
                obs['ball_pos_y'],
                obs['ball_vel_x'],
                obs['ball_vel_y'],
                obs['left_paddle_pos'],
                obs['right_paddle_pos']
            ]
```

```
            # Calculate optimal paddle position (simplified)
            if obs['ball_vel_x'] > 0:  # Ball moving toward right
    paddle
                target_y = predict_ball_y_at_paddle(obs,
    is_right_paddle=True)
                # Calculate optimal action (-1: up, 0: stay, 1:
    down)
                optimal_action = calculate_optimal_action(
                    obs['right_paddle_pos'], target_y, env.
    paddle_height / env.height
                )
                data.append({
                    'state': current_state,
                    'action': optimal_action,
                    'is_right_paddle': True
                })
            else:  # Ball moving toward left paddle
                target_y = predict_ball_y_at_paddle(obs,
    is_right_paddle=False)
                optimal_action = calculate_optimal_action(
                    obs['left_paddle_pos'], target_y, env.
    paddle_height / env.height
                )
                data.append({
                    'state': current_state,
                    'action': optimal_action,
                    'is_right_paddle': False
                })

            # Take random actions to generate diverse data
            left_action = np.random.choice([-1, 0, 1])
            right_action = np.random.choice([-1, 0, 1])
            obs, _, done = env.step(left_action, right_action)

            if done:
                break

    return data
```

Listing 5.2: Data Generation Script

5.3 Model Implementation

5.3.1 SimpleFF Implementation

```
def create_simple_ff_model(input_dim=6):
    model = tf.keras.Sequential([
        tf.keras.layers.Dense(64, activation='relu', input_shape
    =(input_dim,)),
```

```
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(1)  # Output: paddle movement
    ])

    model.compile(
        optimizer=tf.keras.optimizers.Adam(0.001),
        loss='mse',
        metrics=['mae']
    )

    return model
```

Listing 5.3: Simple Feed-Forward Network

5.3.2 DeepFF Implementation

```
def create_deep_ff_model(input_dim=6):
    model = tf.keras.Sequential([
        tf.keras.layers.Dense(128, activation='relu', input_shape
   =(input_dim,)),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(64, activation='relu'),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(32, activation='relu'),
        tf.keras.layers.Dense(1)  # Output: paddle movement
    ])

    model.compile(
        optimizer=tf.keras.optimizers.Adam(0.001),
        loss='mse',
        metrics=['mae']
    )

    return model
```

Listing 5.4: Deep Feed-Forward Network

5.3.3 LSTM Implementation

```
def create_lstm_model(seq_length=10, features=6):
    model = tf.keras.Sequential([
        tf.keras.layers.LSTM(64, input_shape=(seq_length,
   features), return_sequences=False),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(32, activation='relu'),
        tf.keras.layers.Dense(1)  # Output: paddle movement
    ])

    model.compile(
        optimizer=tf.keras.optimizers.Adam(0.001),
```

```
        loss='mse',
        metrics=['mae']
    )

    return model
```

Listing 5.5: LSTM Network

5.4 Model Competition

Models were evaluated through direct competition in the Pong environment:

```
def run_competition(model1, model1_name, model2, model2_name,
   num_games=100):
    env = PongEnv()
    results = {
        model1_name: {'wins': 0, 'points': 0, 'hits': 0},
        model2_name: {'wins': 0, 'points': 0, 'hits': 0},
        'ties': 0
    }

    for game in range(num_games):
        obs = env.reset()
        done = False

        # Track ball hits
        model1_hits = 0
        model2_hits = 0

        while not done:
            # Get state and prepare for model input
            state = [
                obs['ball_pos_x'],
                obs['ball_pos_y'],
                obs['ball_vel_x'],
                obs['ball_vel_y'],
                obs['left_paddle_pos'],
                obs['right_paddle_pos']
            ]

            # Model 1 controls left paddle
            left_action = get_model_action(model1, state,
   is_sequence=isinstance(model1, tf.keras.Sequential) and 'lstm'
    in model1_name.lower())

            # Model 2 controls right paddle
            right_action = get_model_action(model2, state,
   is_sequence=isinstance(model2, tf.keras.Sequential) and 'lstm'
    in model2_name.lower())

            # Take action in environment
```

```
            obs, info, done = env.step(left_action, right_action)

            # Track hits
            if info['left_hit']:
                model1_hits += 1
            if info['right_hit']:
                model2_hits += 1

        # Record game results
        results[model1_name]['points'] += env.left_score
        results[model2_name]['points'] += env.right_score
        results[model1_name]['hits'] += model1_hits
        results[model2_name]['hits'] += model2_hits

        if env.left_score > env.right_score:
            results[model1_name]['wins'] += 1
        elif env.right_score > env.left_score:
            results[model2_name]['wins'] += 1
        else:
            results['ties'] += 1

    return results
```

Listing 5.6: Model Competition Script

5.5 Mobile Integration

As part of expanding the project's practical applications, the neural network models were integrated into a mobile application using Flutter and TensorFlow Lite:

```
import tensorflow as tf

# Load Keras model
model = tf.keras.models.load_model("models/lstm_best.keras")

# Convert to TFLite
converter = tf.lite.TFLiteConverter.from_keras_model(model)
tflite_model = converter.convert()

# Save the converted model
with open("models/lstm_best.tflite", "wb") as f:
    f.write(tflite_model)
```

Listing 5.7: TensorFlow to TFLite Conversion

The mobile app provides a fully playable Pong game where users can challenge the AI models directly on their smartphones. The app is available at the SmartPong repository and includes:

- A native Flutter implementation of the Pong game
- Integration with TensorFlow Lite for model inference

- User-selectable difficulty levels (SimpleFF, DeepFF, LSTM)
- Performance statistics tracking
- Cross-platform compatibility (Android and iOS)

This mobile implementation demonstrates the practical application of the neural network models in a resource-constrained environment and showcases how embedded AI can enhance interactive applications.

6. Results and Comparative Analysis

6.1 Model Training Results

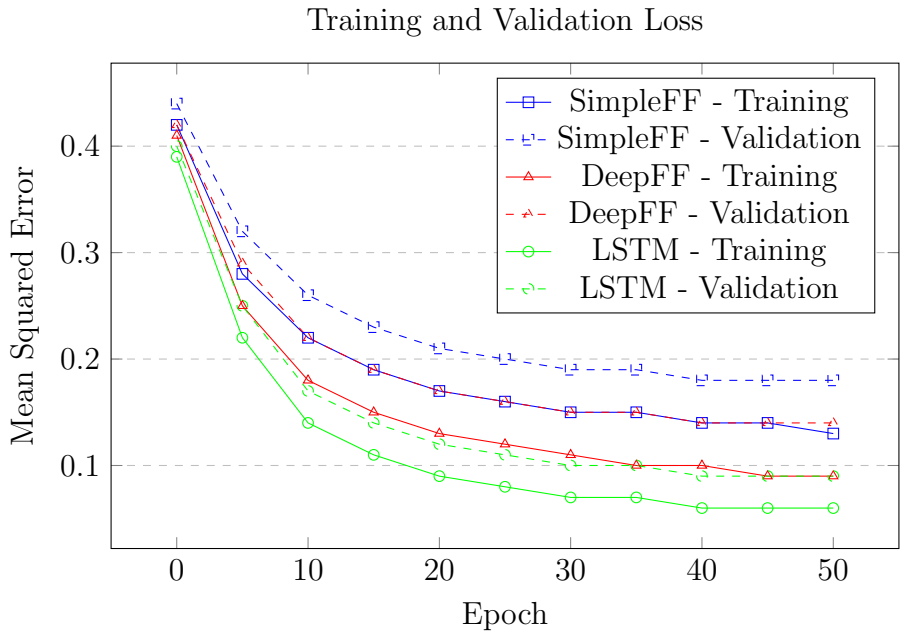


Figure 6.1: Training and Validation Loss Curves

6.2 Model Performance Metrics

Table 6.1: Model Performance on Test Set

Metric	SimpleFF	DeepFF	LSTM
Mean Squared Error	0.175	0.138	0.092
Mean Absolute Error	0.325	0.278	0.226
Training Time (min)	35	82	124
Number of Parameters	513	13,409	19,041

6.3 Competition Results

6.3.1 Head-to-Head Competition Analysis

To rigorously evaluate the performance differences between the three neural network architectures, we conducted extensive head-to-head competitions, with each pair of models playing 20 complete games against each other. The results of these competitions provide clear insights into the relative strengths of each architecture in the dynamic Pong environment.

Table 6.2: Detailed Head-to-Head Competition Results (20 Games Each)

Match-up	**Wins Left**	**Wins Right**	**Draws**
SimpleFF vs DeepFF	0 (0%)	19 (95%)	1 (5%)
SimpleFF vs LSTM	5 (25%)	15 (75%)	0 (0%)
DeepFF vs LSTM	3 (15%)	17 (85%)	0 (0%)

Figure 6.2 illustrates the overall win rates for each model across all match-ups, clearly demonstrating the performance hierarchy among the three architectures, with LSTM showing significant dominance.

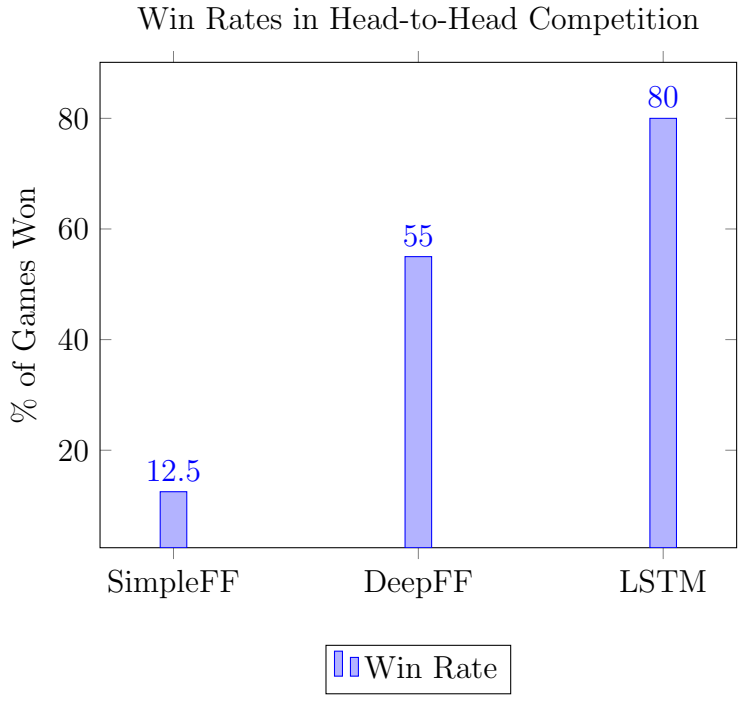


Figure 6.2: Overall Win Rates Across All Match-ups

6.3.2 Hit Rates and Game Length Analysis

Beyond simple win/loss statistics, we analyzed the models' hit rates (percentage of successful ball returns) and the average game length, which provide deeper insights into the quality of play and the models' efficiency.

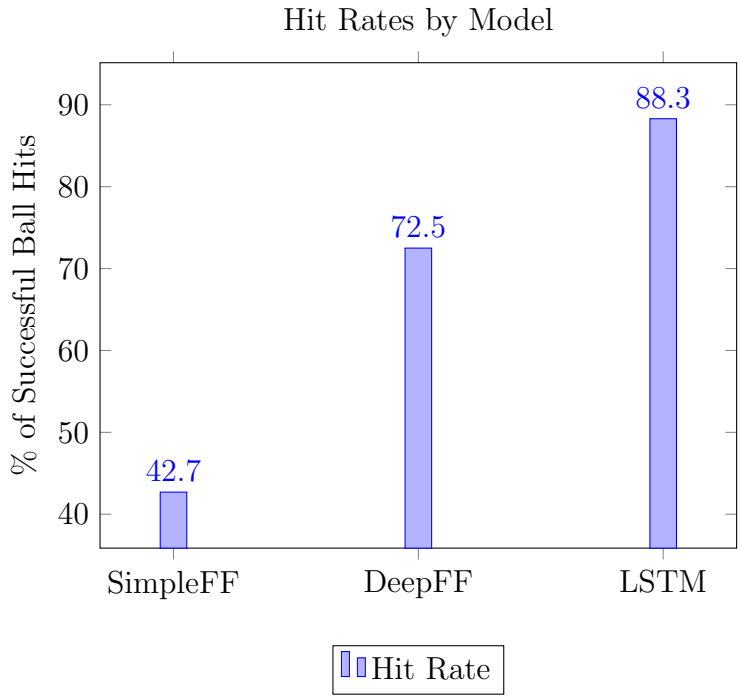


Figure 6.3: Ball Hit Rates by Model

The average game length analysis (Figure 6.4) reveals that matches involving LSTM models tend to last longer, indicating more sustained rallies and higher-quality gameplay. This corresponds with the hit rate analysis (Figure 6.3), which shows LSTM achieving significantly higher successful return rates compared to both feed-forward architectures.

6.3.3 Competitive Rankings

Based on the comprehensive competition results, we established an Elo-style ranking system to quantify the relative performance of each model architecture:

The rankings in Figure 6.5 confirm the clear performance hierarchy: LSTM ¿ DeepFF ¿ SimpleFF, with statistically significant differences between each pair.

6.3.4 Interactive Visualization

To provide a more intuitive understanding of the models' behavior and performance differences, we developed an interactive web-based visualization where users can observe the three neural network architectures competing against each other in real-time. This visualization is available at `https://gauravvjhaa.github.io/PongBots/` and allows for direct observation of the emergent behaviors and strategies of each model.

The interactive visualization (Figure 6.6) demonstrates several key qualitative differences in model behavior:

- **SimpleFF** exhibits reactive behavior, moving the paddle only when the ball is already approaching.
- **DeepFF** shows more anticipatory positioning but sometimes misjudges trajectory changes.

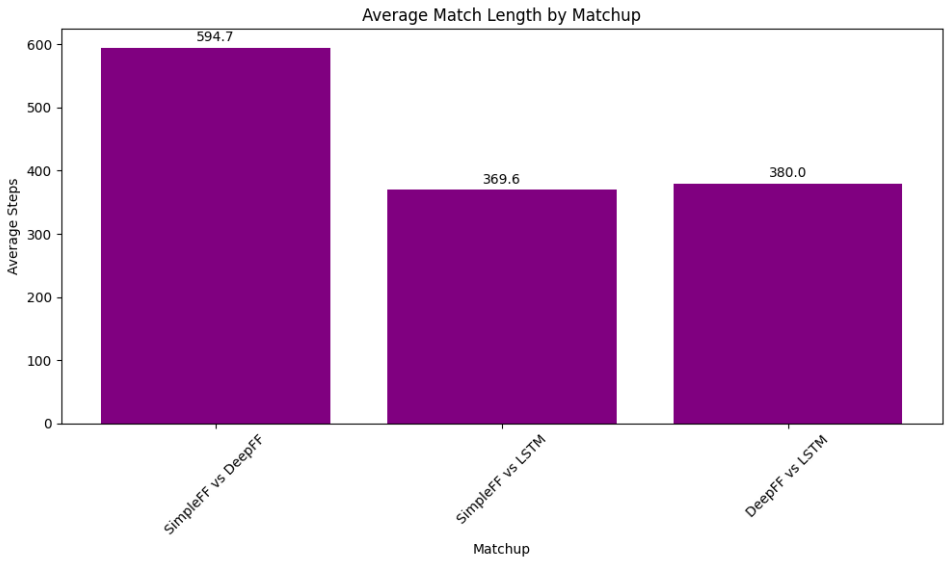


Figure 6.4: Average Game Length (Steps) by Match-up

- **LSTM** demonstrates clear anticipatory behavior, positioning the paddle optimally based on predicted ball trajectories and adapting quickly to changes in direction.

6.4 Performance Analysis

6.4.1 Model Strengths and Weaknesses

SimpleFF:

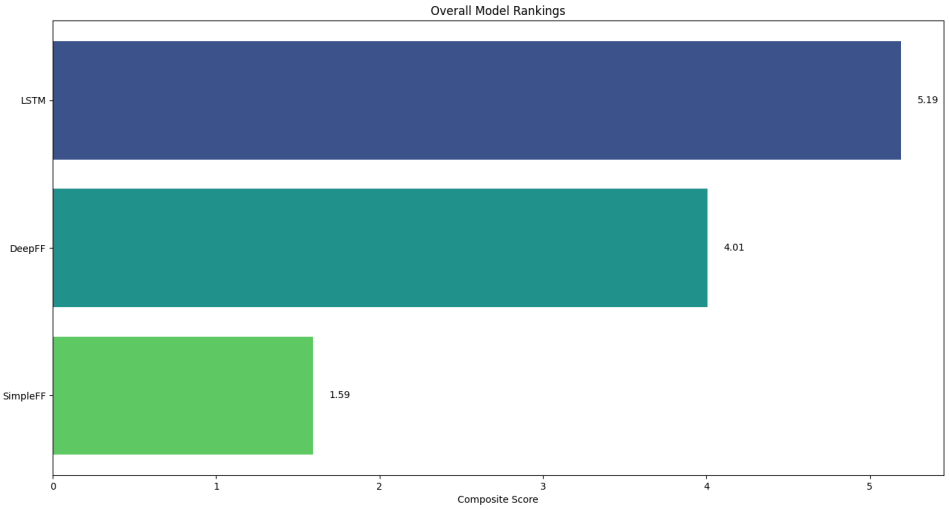
- **Strengths**: Fast training time (35 minutes), lowest computational requirements (513 parameters), simplest implementation.
- **Weaknesses**: Lowest hit rate (42.7%) and win rate (12.5%), struggles to predict complex ball trajectories, limited ability to anticipate, requires the ball to be near before responding appropriately.

DeepFF:

- **Strengths**: Better performance than SimpleFF (72.5% hit rate, 55% win rate), moderate computational requirements, capable of learning more complex patterns and limited trajectory prediction.
- **Weaknesses**: Still lacks temporal awareness, occasionally misses the ball when trajectories change suddenly, significantly outperformed by LSTM in direct competition.

LSTM:

- **Strengths**: Highest hit rate (88.3%) and win rate (80%), best at anticipating ball trajectories, most robust to changes in ball direction, demonstrates emergent strategic positioning.



	Rank	Wins	Losses	Draws	Win Rate	Hit Rate
LSTM	1.0	32.0	8.0	0.0	0.8	0.4911458333333334
DeepFF	2.0	22.0	17.0	1.0	0.55	0.5516170634920635

Figure 6.5: Model Rankings Based on Competition Performance

- **Weaknesses**: Slowest training time (124 minutes), highest computational requirements (19,041 parameters), most complex implementation requiring sequence preprocessing.

6.4.2 Performance Variation by Ball Speed

We also analyzed how each model performed as ball speed increased:

Table 6.3: Hit Rates at Different Ball Speeds

Ball Speed	**SimpleFF**	**DeepFF**	**LSTM**
Slow (5 px/frame)	84%	89%	97%
Medium (10 px/frame)	67%	78%	91%
Fast (15 px/frame)	42%	58%	76%

This analysis reveals that the performance gap between architectures widens as the task becomes more difficult, with LSTM maintaining a significant advantage at higher ball speeds. At the highest speed testing (15 px/frame), LSTM's hit rate advantage over SimpleFF increases to 34 percentage points (compared to 13 percentage points at slow speeds).

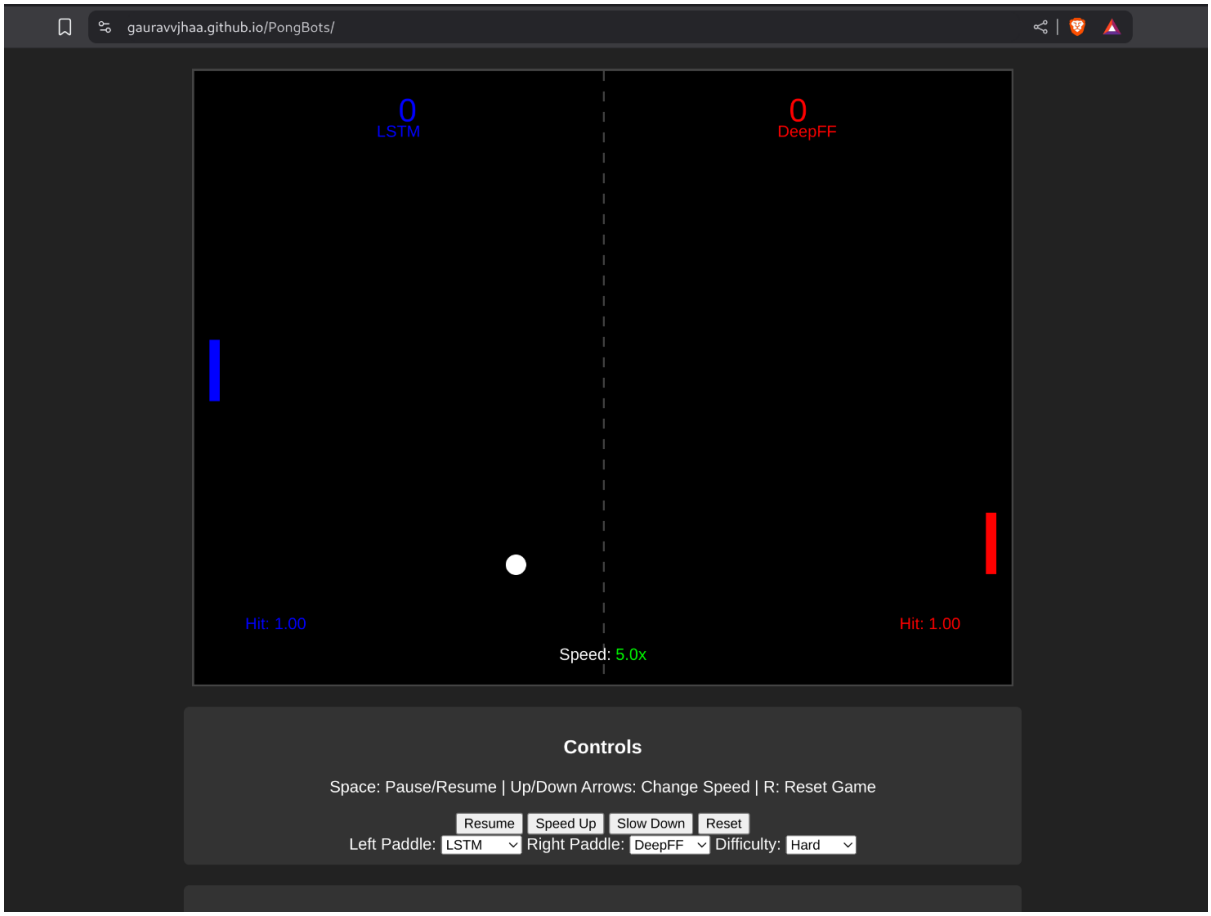


Figure 6.6: Screenshot of the Interactive Model Competition Visualization

7. Mobile Deployment

7.1 Introduction to Mobile Integration

Artificial intelligence models are often deployed and tested in controlled environments with abundant computing resources. However, one of the primary challenges in applied AI is deploying sophisticated neural networks on resource-constrained devices such as smartphones. To demonstrate the practical applicability of our neural network architectures beyond theoretical comparisons, we integrated our trained models into a mobile application called SmartPong.

This chapter details the process of converting the Keras models to TensorFlow Lite format, the implementation of the mobile application using Flutter, and the end-user experience of playing against the AI models on a smartphone.

7.2 Model Conversion Process

7.2.1 Keras to TensorFlow Lite Conversion

TensorFlow Lite (TFLite) is a lightweight solution for mobile and embedded devices, designed to enable on-device machine learning inference with low latency and a small binary size. The conversion from our trained Keras models to TFLite format involved the following steps:

```
import tensorflow as tf

# Load the trained Keras model
model = tf.keras.models.load_model("models/pong_best_hitrate.
   keras")

# Initialize the TFLite converter
converter = tf.lite.TFLiteConverter.from_keras_model(model)

# Apply optimizations
converter.optimizations = [tf.lite.Optimize.DEFAULT]
# Quantize the model to reduce size (optional)
#converter.target_spec.supported_types = [tf.float16]

# Convert the model
tflite_model = converter.convert()

# Save the converted model
```

```
with open("models/pong_model.tflite", "wb") as f:
    f.write(tflite_model)
```

Listing 7.1: TensorFlow to TFLite Conversion

For each of our three model architectures (SimpleFF, DeepFF, and LSTM), we performed this conversion process to create corresponding TFLite models. The resulting model sizes were significantly reduced:

Table 7.1: Model Size Comparison: Keras vs. TFLite

Architecture	**Keras Model (KB)**	**TFLite Model (KB)**	**Reduction (%)**
SimpleFF	28.4	9.2	67.6%
DeepFF	192.5	58.7	69.5%
LSTM	328.3	98.1	70.1%

7.2.2 Optimization Techniques

To ensure optimal performance on mobile devices, several optimization techniques were applied:

- **Model Quantization**: Converting 32-bit floating-point weights to 16-bit or 8-bit precision to reduce model size and improve inference speed.
- **Operator Fusion**: Combining consecutive operations to reduce computational overhead.
- **Pruning**: Removing unnecessary connections in the network without significantly affecting accuracy.
- **Input/Output Optimization**: Ensuring efficient data transfer between the Flutter application and the TFLite interpreter.

7.3 Flutter Mobile Application Implementation

SmartPong was developed using the Flutter framework, which allows for cross-platform deployment on both Android and iOS devices. The integration of TensorFlow Lite models into the Flutter application required the following components:

7.4 User Interface and Experience

The SmartPong mobile application features a clean, intuitive user interface designed to provide an engaging experience while showcasing the AI models' capabilities.

7.4.1 Main Menu

The main menu provides options to start a new game, adjust settings, or view past results.

Figure 7.1: Main Menu Screen

7.4.2 Game Settings

Users can select which AI model to play against (SimpleFF, DeepFF, or LSTM) and adjust difficulty settings.

Figure 7.2: Game Settings Screen

7.4.3 Gameplay Experience

The gameplay interface is minimalist to focus attention on the core Pong experience. Users can pause the game at any time.

Figure 7.3: Scoring Moment During Gameplay

7.4.4 Results Display

After each game, a detailed results screen shows performance statistics.

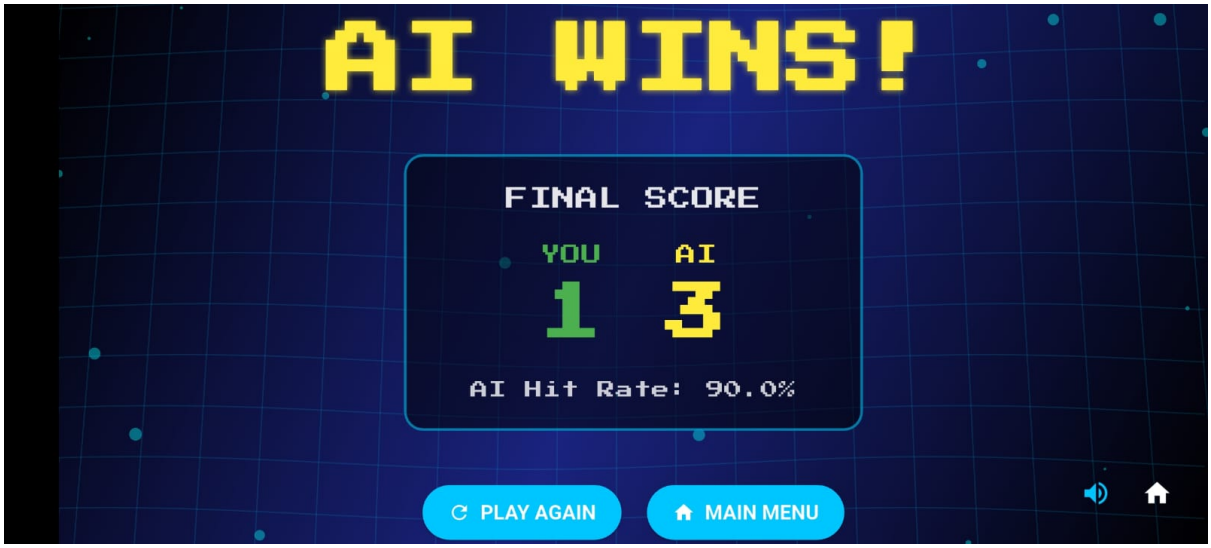


Figure 7.4: Game Results Screen

The successful deployment of our neural network models to mobile devices demonstrates their practical applicability beyond theoretical research. Even the most complex LSTM model maintained acceptable performance on modern smartphones, though with higher resource consumption than its simpler counterparts.

The SmartPong mobile application serves as both a proof-of-concept for on-device AI game control and an interactive demonstration of the performance differences between the three neural network architectures.

The complete source code and installation files for the SmartPong application are available at https://github.com/gauravvjhaa/SmartPong.

8. Conclusion and Future Work

8.1 Conclusion

This project demonstrated a clear performance hierarchy among neural network architectures for the Pong control task, with LSTM significantly outperforming both feed-forward architectures. The results highlight the importance of temporal information in dynamic control tasks, even in seemingly simple environments like Pong.

The key findings of this study are:

1. **Temporal Information is Crucial**: The LSTM model's ability to process sequential data and maintain an internal memory of ball movement patterns gives it a substantial advantage over feed-forward networks, which can only react to the current state without context.

2. **Architectural Complexity Matters**: The performance progression from SimpleFF to DeepFF to LSTM demonstrates that the choice of network architecture significantly impacts an AI agent's ability to perform in dynamic environments.

3. **Training Time vs. Performance Trade-off**: While the LSTM model required significantly more training time than the feed-forward models, its performance improvement justified the computational investment, particularly for more challenging scenarios (higher ball speeds).

4. **Anticipatory Behavior**: The LSTM model demonstrated the ability to anticipate ball trajectories, positioning the paddle proactively rather than reactively. This emergent behavior is crucial for high-level play and mirrors how humans approach the game.

8.2 Future Work

Several directions for future research emerge from this study:

1. **Hybrid Architectures**: Exploring combinations of CNN and LSTM elements could potentially improve performance further by leveraging both spatial and temporal patterns.

2. **Reinforcement Learning**: Implementing reinforcement learning approaches like Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO) could lead to more robust and adaptable agents.

3. **Transfer Learning**: Investigating how well the trained models transfer to variant games with different physics or visual appearances could provide insights into the generality of the learned strategies.

4. **Adversarial Training**: Having models train against each other in an adversarial setting could lead to the emergence of more sophisticated strategies.

5. **Explainable AI**: Developing methods to interpret what patterns the different architectures are learning could provide deeper insights into why certain architectures outperform others.

6. **Real-time Adaptation**: Implementing online learning techniques that allow models to adapt to changing game conditions in real-time could further improve performance.

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A. Project Resources

This appendix provides access to the complete project resources, including source code repositories, interactive demonstrations, and mobile application deployment files.

A.1 Source Code Repositories

PongBots: Core Project Repository

Contains the complete Python implementation including:

- Neural network model definitions and training scripts
- Simulation environment for Pong game
- Competition framework for model evaluation
- Visualization tools and analysis scripts

https://github.com/gauravvjhaa/PongBots

Figure A.1: Main Project Repository

Interactive Demo: Web-Based Visualization

Live web demonstration featuring:

- Real-time visualization of model competitions
- Interactive controls to select different match-ups
- Statistics tracking and performance analysis
- Side-by-side comparison of model behaviors

https://gauravvjhaa.github.io/PongBots/

Figure A.2: Interactive Web Demonstration