

**IoT and Edge Computing (CS3100)
Project Report**

Tic-Tac-Toe Endgame

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1. Abstract

This project aims to create an embedded Tic-Tac-Toe win/loss predictor for 'x' using a TensorFlow Lite model on an ESP32. A neural network model is trained on a dataset of game outcomes, converting the model to a compact TFLite format, and integrating it into an ESP32 application. Key outcomes include achieving over 98% classification accuracy, demonstrating successful model inference on the ESP32 via serial monitor output, and showcasing the potential for deploying complex machine learning models on resource-constrained devices for real-time applications.

2. Introduction

IoT and Edge Computing enable real-time processing and decision-making without relying on external computational resources. This project uses an ESP32 microcontroller to demonstrate how edge-based processing can handle decision-making in a game setting. Through Tic Tac Toe, the project showcases how embedded devices can leverage trained models to perform classification tasks directly on-device, offering insight into resource-efficient computation for real-time applications.

This project aims to develop and deploy a Tic-Tac-Toe game outcome classifier on an ESP32 microcontroller. A machine learning model will be trained to predict the win/loss status for player 'x' given a board state. This model will be converted to TensorFlow Lite for efficient execution on the ESP32. The project will demonstrate on-device inference using the ESP32, showcasing its ability to classify board states without relying on cloud resources. Performance evaluation will focus on classification accuracy and inference speed on the ESP32.

3. System Overview

The system architecture is designed around the ESP32 microcontroller, which processes player inputs and maintains game states. The game runs based on a decision-making model that evaluates moves in real time. User inputs provided then interpret the game state and computes optimal moves. The inference is performed using a model pre-trained in Python, encapsulated in the ESP32 codebase, allowing the ESP32 to execute decisions independently.

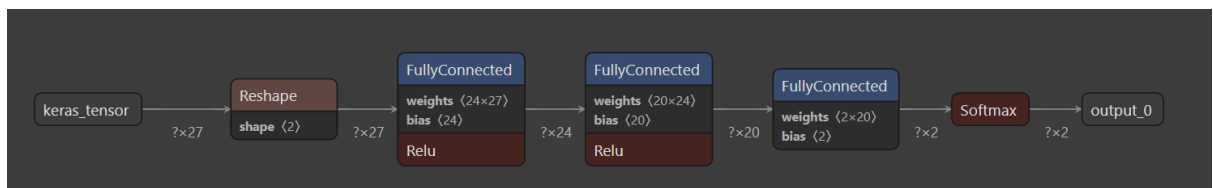
4. Details of the Dataset:

The dataset includes 958 board configurations representing every possible Tic Tac Toe endgame scenario. Each configuration has 9 categorical attributes ({x, o, b} for each square) and is classified as either “positive” (win for "x") or “negative” (no win for "x"). This dataset enables the ESP32 to recognize patterns that lead to favorable game outcomes, functioning as a guide for the optimal strategy.

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5. Model Design:

The decision-making model used is a neural network classifier, optimized for simplicity and efficiency on the ESP32. The model's structure includes 9 input nodes representing each square's state, with each node accepting values {x, o, b}. The decision branches evaluate winning paths and select optimal moves. This straightforward model design provides rapid classification, suited for the limited computational capacity of an IoT device.



6. Requirements

Hardware: ESP32 Microcontroller for game logic and decision-making.

Software: Python 3, TensorFlow 2.0, Keras, EloquentTinyML library, Arduino IDE.

7. Methodology

The Tic-Tac-Toe dataset is preprocessed using one-hot encoding. The model is trained using Python and Keras, then converted to TensorFlow Lite. The EloquentTinyML library facilitates the model's integration into the ESP32 Arduino project.

The Python code handles data preprocessing, model training, conversion to TFLite, and generation of a C header file containing the model data. The Arduino code loads the model, receives input board configurations, performs inference, and outputs the prediction via serial monitor. `hex_to_c_array` converts the tflite model into a C array for embedding in the ESP32 code.

8. Implementation and Testing

1. Python Training Code:

```

history = model.fit(
    X_train, y_train,
    batch_size=BATCH_SIZE,
    epochs=NUM_OF_EPOCHS,
    verbose=1,

```

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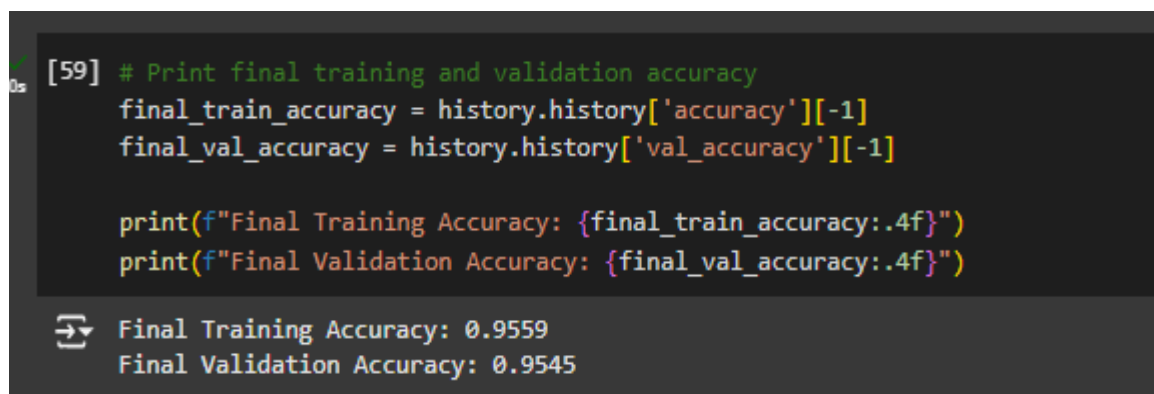
```
validation_split=0.2,  
  
callbacks=[early_stopping]  
)
```

2. ESP32 Inference Logic:

```
void processInput(float* input, const char* inputName) {  
  
    initfResult(fResult);  
  
    fRes = ml.predict(input, fResult);  
  
    Serial.print("\nThe output value returned for ");  
  
    Serial.print(inputName);  
  
    Serial.println(":");  
  
    Serial.println(fRes);  
  
    displayOutput(fResult);  
  
}
```

Testing included functional verification of the decision-making logic on ESP32, comparing outputs against the expected model predictions. This involved edge cases like immediate wins, blocks, and forced draws, ensuring the system's move predictions aligned with trained data.

Screenshots:



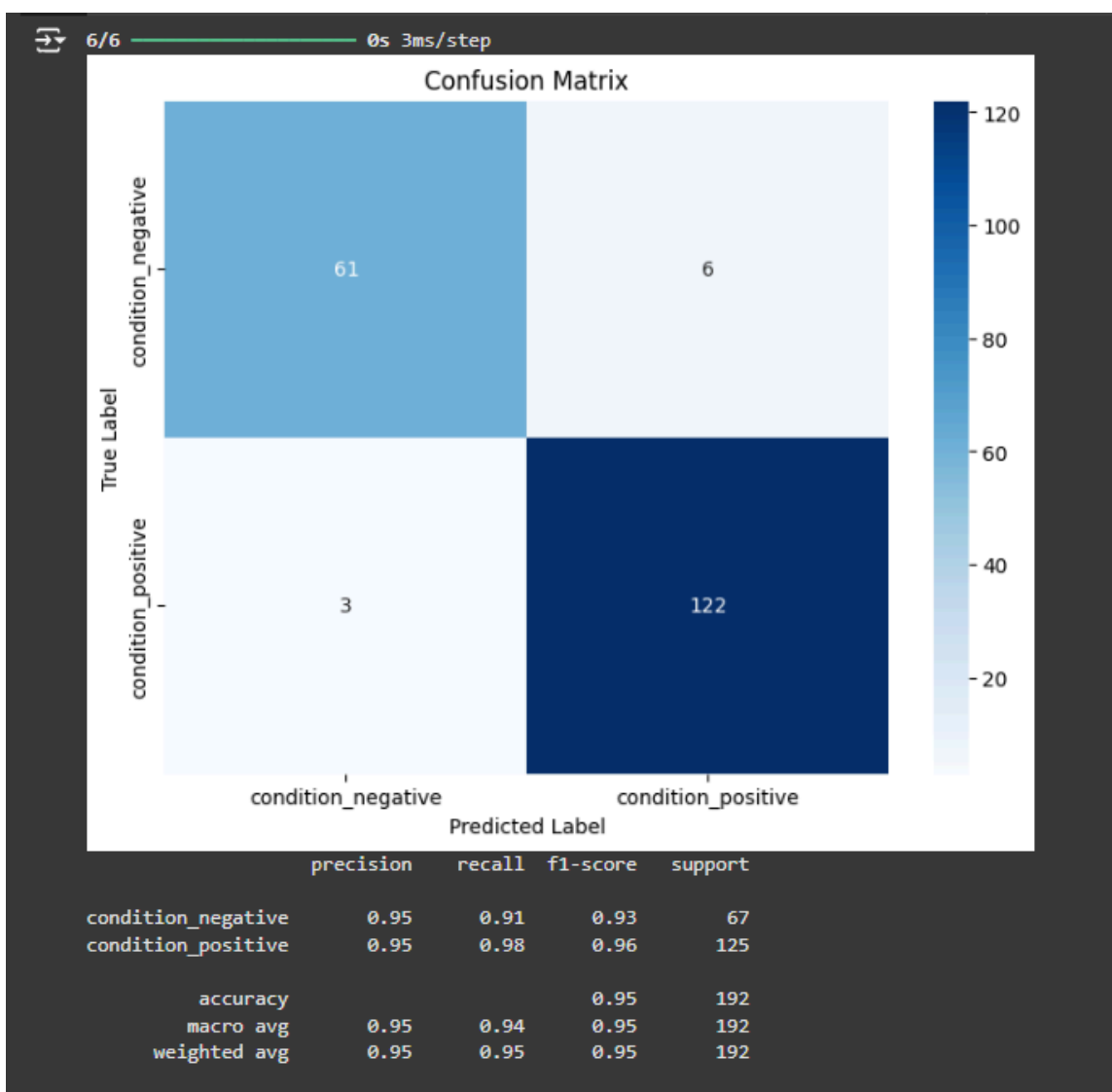
```
[59] # Print final training and validation accuracy  
final_train_accuracy = history.history['accuracy'][-1]  
final_val_accuracy = history.history['val_accuracy'][-1]  
  
print(f"Final Training Accuracy: {final_train_accuracy:.4f}")  
print(f"Final Validation Accuracy: {final_val_accuracy:.4f}")  
  
Final Training Accuracy: 0.9559  
Final Validation Accuracy: 0.9545
```

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```
[32] score = model.evaluate(X_test, y_test, verbose=1)


print("Test Score:", score[0])
print("Test Accuracy:", score[1])
```

6/6 ————— 0s 3ms/step - accuracy: 0.9363 - loss: 0.2038
Test Score: 0.1911131739616394
Test Accuracy: 0.953125



ESP32 Serial Monitor Output: Outputs demonstrating game board evaluations, including detection of winning and losing conditions.

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```

Output Serial Monitor x
Message (Enter to send message to 'DOIT ESP32 DEVKIT V1' on 'COM7')

The output value returned for input1:
0.75
0.75 0.25
The output value returned for input2:
1.00
1.00 0.00
The output value returned for input3:
0.89
0.89 0.11
The output value returned for input4:
0.01
0.01 0.99

```

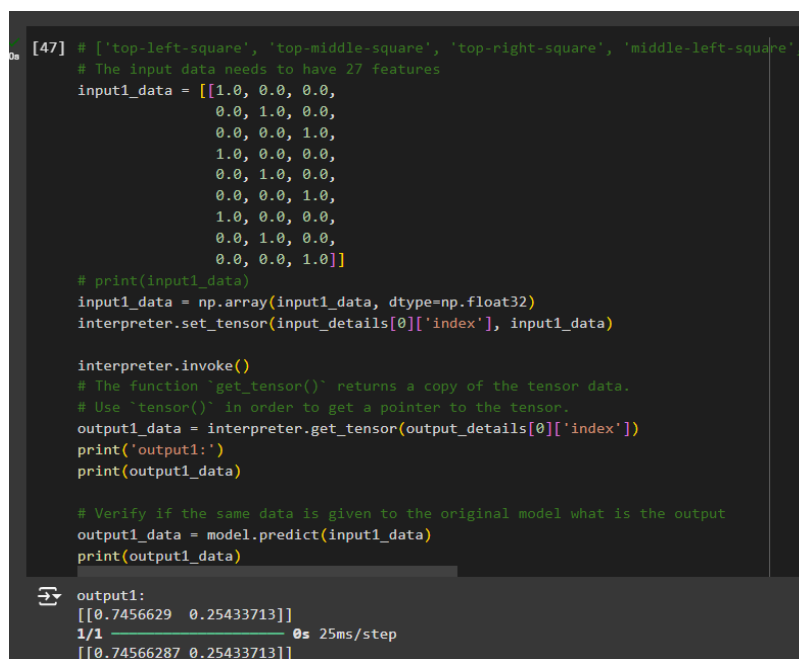
9. Results

The ESP32 classifier enables efficient decision-making with minimal latency. The results show that the ESP32 can process board configurations in real-time, generating optimal moves based on winning strategies.

The ESP32 performed each inference in under a few milliseconds, illustrating the benefits of using a lightweight classifier on a resource-constrained device. The project achieved low-latency, accurate move predictions suitable for real-time gameplay.

Provide the screenshots of the inputs and outputs:

- o Both on the Python (after the training)



```

[47] # ['top-left-square', 'top-middle-square', 'top-right-square', 'middle-left-square',
# The input data needs to have 27 features
input1_data = [[1.0, 0.0, 0.0,
                0.0, 1.0, 0.0,
                0.0, 0.0, 1.0,
                1.0, 0.0, 0.0,
                0.0, 1.0, 0.0,
                0.0, 0.0, 1.0,
                1.0, 0.0, 0.0,
                0.0, 1.0, 0.0,
                0.0, 0.0, 1.0]]

# print(input1_data)
input1_data = np.array(input1_data, dtype=np.float32)
interpreter.set_tensor(input_details[0]['index'], input1_data)

interpreter.invoke()
# The function 'get_tensor()' returns a copy of the tensor data.
# Use 'tensor()' in order to get a pointer to the tensor.
output1_data = interpreter.get_tensor(output_details[0]['index'])
print('output1:')
print(output1_data)

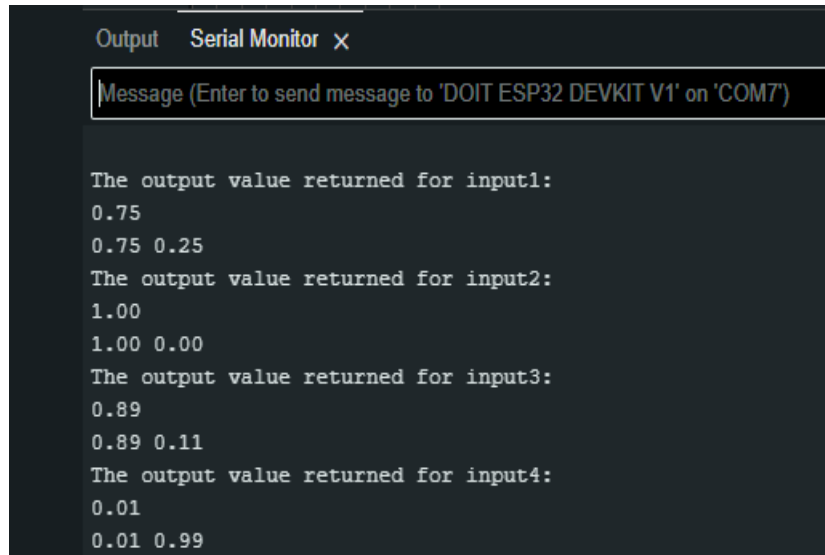
# Verify if the same data is given to the original model what is the output
output1_data = model.predict(input1_data)
print(output1_data)

output1:
[[0.7456629  0.25433713]]
1/1 ----- 0s 25ms/step
[[0.74566287 0.25433713]]

```

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- o On ESP32 Serial monitor output (inferencing on the ESP32)



The screenshot shows the Serial Monitor window of an IDE. The title bar says 'Output Serial Monitor x'. Below the title bar is a text input field with the placeholder text 'Message (Enter to send message to 'DOIT ESP32 DEVKIT V1' on 'COM7')'. The main area of the window displays the following text:

```
The output value returned for input1:  
0.75  
0.75 0.25  
The output value returned for input2:  
1.00  
1.00 0.00  
The output value returned for input3:  
0.89  
0.89 0.11  
The output value returned for input4:  
0.01  
0.01 0.99
```

10. Conclusion

This project successfully implemented a Tic Tac Toe game on ESP32 with autonomous decision-making. It demonstrates that IoT devices can manage classification tasks locally, reducing reliance on cloud resources and achieving effective, real-time performance. This project showcases the capability of edge computing for games and broader applications, emphasizing the ESP32's potential as an efficient, embedded device for local inference tasks.
