# A Hybrid Deep Learning Framework For Detecting Phishing Websites

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# Presentation Structure

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Introduction

# Background

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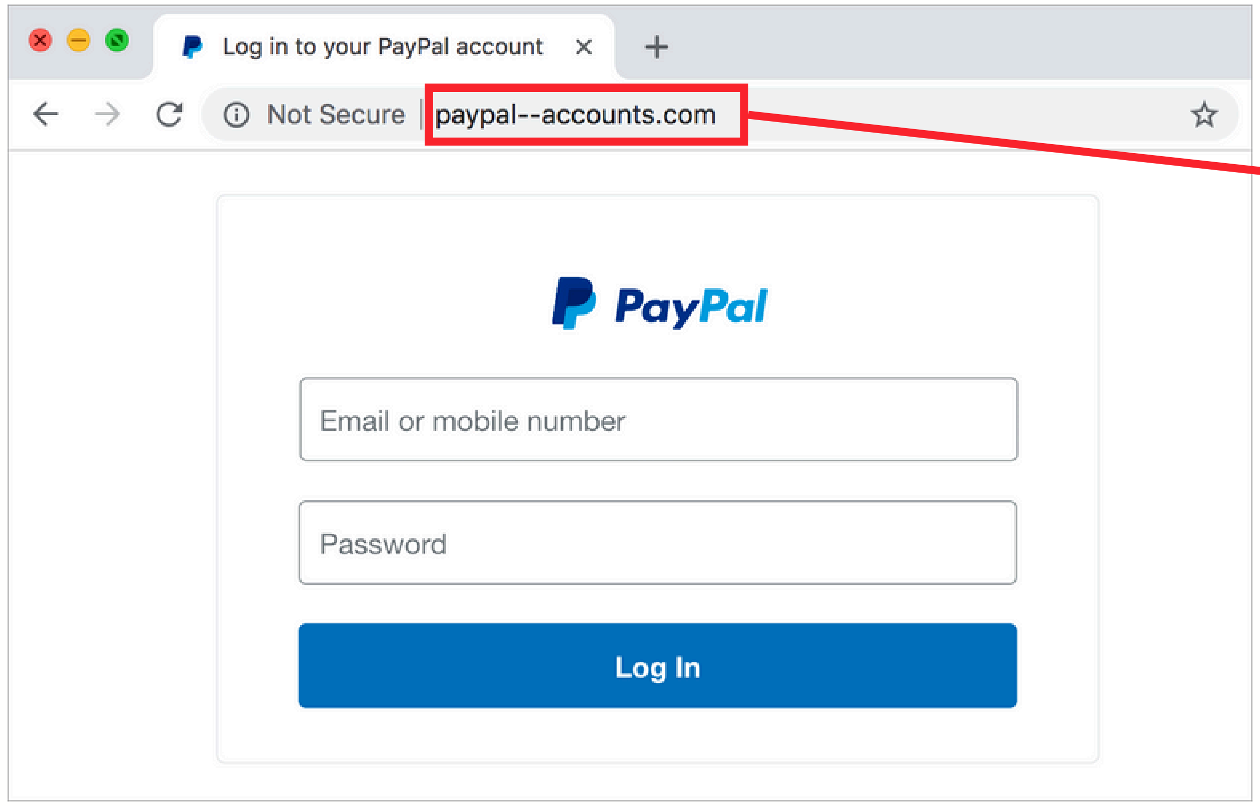
Phishing is the practice of masquerading malicious websites as legitimate.

- Purpose is to exploit user trust to steal personal information. [1]




Phished Website URL!

- Similar layout, color schemes, etc BUT different URL! [2]
- Modern attacks create more dynamic and sophisticated phishing URLs. [3]

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Introduction

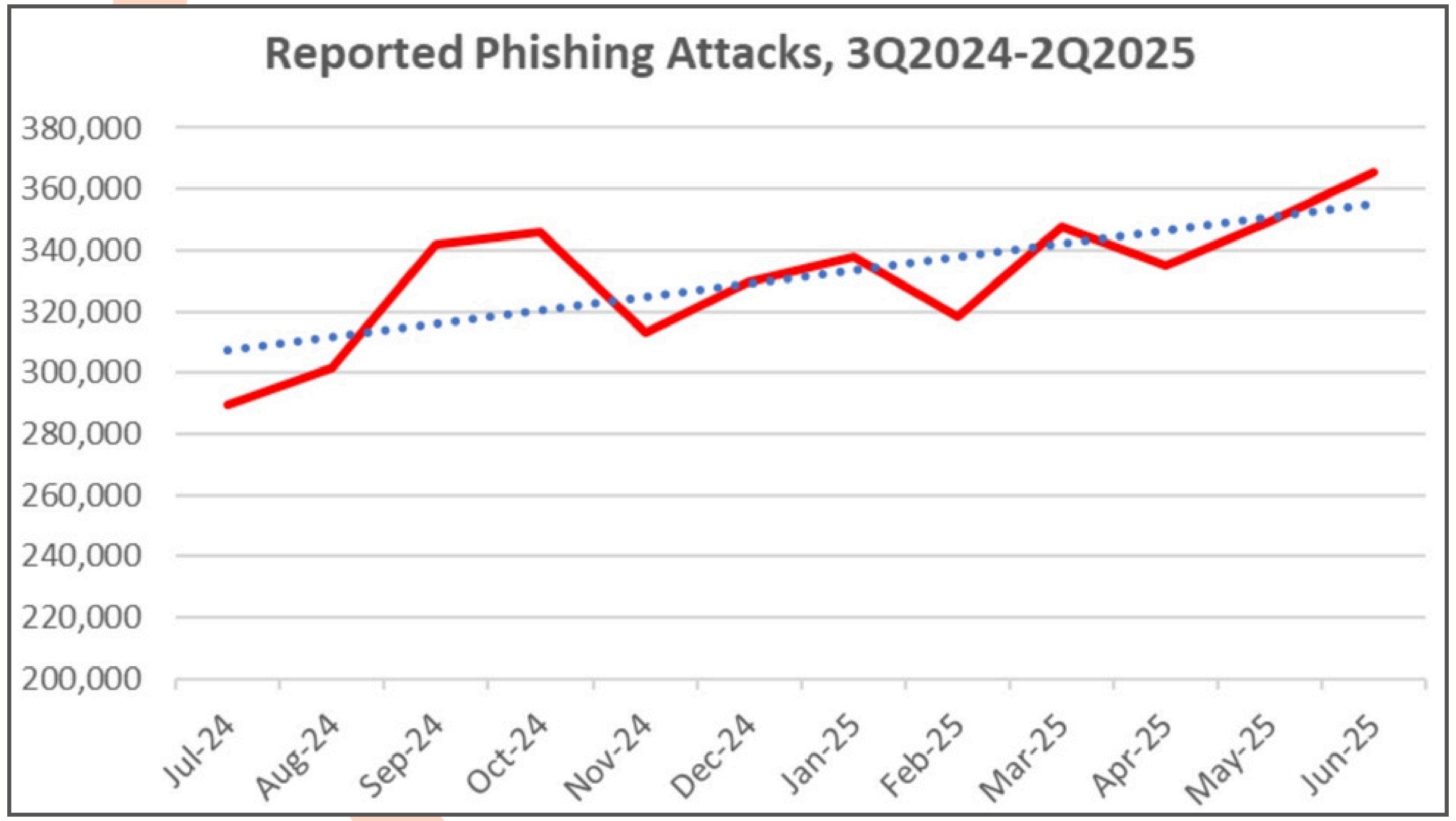
# Motivation

### Phishing Activity Trends Report 2025 [4]

- 2 Million attacks in first half of 2025.
- Finance, Healthcare, Education and several more sectors targeted.

### Limitations of Traditional Systems

- Struggle to keep up with evolving techniques
- Zero-Day Attacks [5]
- Existing models do not capture lexical patterns and temporal dependencies
    - Proposed Hybrid Framework




Phishing Activity Trends Report for 2025 from Anti-Phishing Working Group [4]

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Existing Works

# List-Based Systems

## Whitelists [6]

- Stores and grants access only to proven legitimate websites
- Limitation: Needs to be constantly updated

## Blacklists [5]

- Denies access to stored proven malicious websites
- Limitation: Vulnerable against Zero-Day Attacks

Existing Works

# Heuristics-Based Systems

- Analyzes technical features and attributes to make predictions [7]
- Works against Zero-Day attacks [8]
- Limitation: Relies on pre-determined algorithms, no learning involved to increase adaptability

Existing Works

# Visual Similarity-Based Systems

- Analyzes screenshots to form predictions
- Extracts layouts and color schemes [9]
- Limitation: Requires significant computation power
- Limitation: Bad layouts can cause large rate of false negatives

Existing Works

# Machine Learning-Based Systems

- Adaptive detection systems that identify patterns and relations from data through different learning techniques to form distinctions.

| Study | Model | Accuracy |
|---|---|---|
| [10] | J48 Decision Tree | 93% |
| [11] | Random Forest | 98.40% |
| [12] | Random Forest | 97.30% |
| [13] | Random Forest | 99.06% |
| [14] | Multilayered Stacked Ensemble Model | 98.90% |
| [15] | GA-based XGBoost | 98.57% |

- **Observations**
  - Strong baseline accuracies
  - Limitation: Relies heavily on strong feature quality. Cannot discover deep hidden patterns from raw data.

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# Deep Learning-Based Systems

- Form of machine learning that automatically learns hierarchical representations from data to capture complex relationships.

| Study | Model | Accuracy |
|---|---|---|
| [16] | CNN | 99% |
| [17] | CNN | 99.20% |
| [18] | RNN-GRU | 99.18% |

- **Observations**
  - CNNs outperform ML models and other DL models
  - CNNs capture lexical and spatial patterns only.
  - GRU captures temporal dependencies.
  - Employment of GRU increased performance of RNN from 74% to 99.18%.
  - **Gap**: Need for hybrid model that captures both spatial patterns and temporal dependencies.

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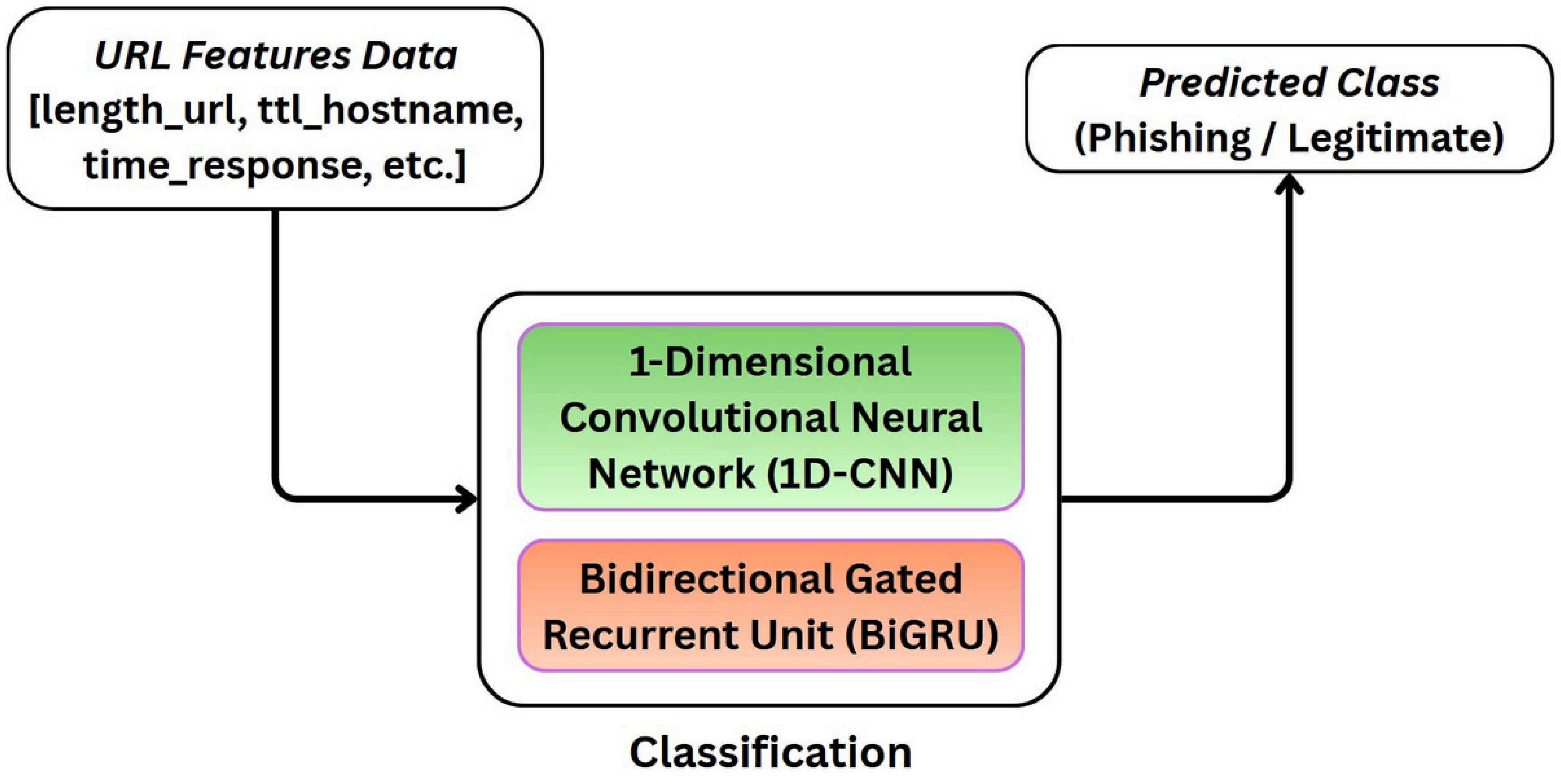
# Proposed Hybrid Framework




- 1D-CNN captures spatial patterns from URL's local lexical features
- BiGRU models the sequential relations, learning dependencies from both directions of the URL.

# Evaluation

- **Datasets**
  - UCI 2015 Dataset [19]
    - 11,055 Websites (4,898 Phishing, 6,157 Legitimate)
    - 31 handcrafted features
  - Mendeley 2020 Dataset [20]
    - 88,647 Websites (30,647 Phishing, 58,000 Legitimate)
    - 111 lexical features

- **Evaluation Metrics**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

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# PLES Considerations

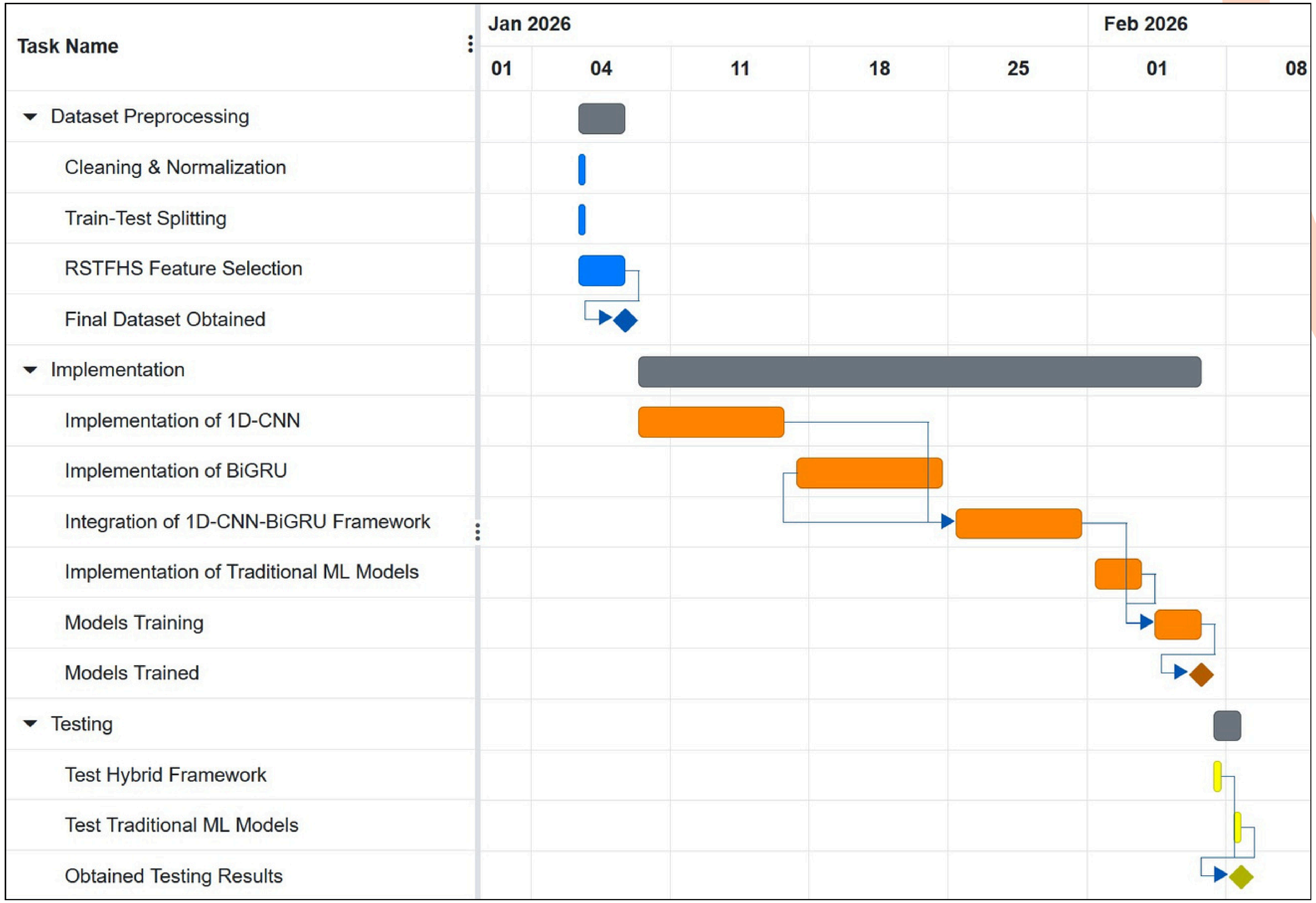
- **Professional**
  - Project adheres to recognized professional standards and principles.
- **Legal**
  - Project complies with relevant data protection regulation.
- **Ethical**
  - Project only uses public technical data, with no user-specific participation or information.
- **Social**
  - Project contributes positively to societal efforts against phishing without pertaining to any other broader social issue.

## Implementation Environment

- Windows 11
- AMD Ryzen 9 5900HX
- NVIDIA GeForce RTX 3050 Ti (4 GB VRAM)
- 32 GB RAM
- 100 GB SSD

# Project Plan

- **Implementation Gantt Chart**



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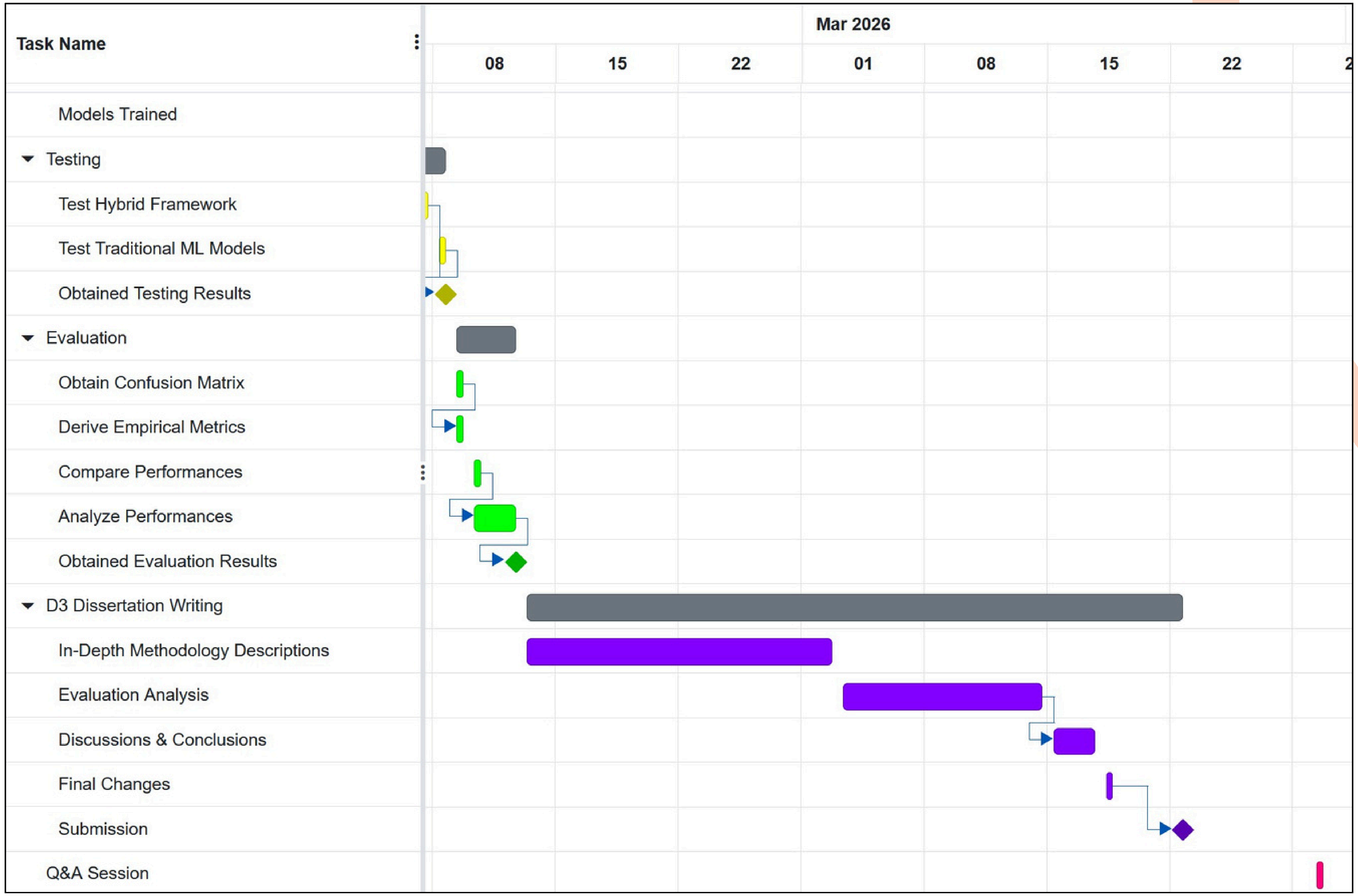
# Project Plan

- **Evaluation & Documentation Gantt Chart**



# Project Plan

- **Major Risks**

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| Risk | Likelihood | Mitigation |
|---|---|---|
| System Failure | Unlikely | Make cloud based backup saves |
| Data Corruption | Unlikely | Make regular local backups |
| Low Performance of Hybrid Framework | Likely | Extensive hyper-parameter tuning |
| Inconsistent Evaluation Results | Possible | Conduct multiple test runs |

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# Thank You