Fault detection in Power Transmission lines

GROUP 13

AIE-C

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Introduction

Power Transmission Systems & Their Vulnerabilities

- Power transmission lines are critical components of modern energy infrastructure.
- Faults such as line-to-line, line-to-ground, and open conductor failures can severely disrupt power delivery.
- Rapid and accurate fault detection is essential to prevent outages, equipment damage, and safety hazards.

◆ Limitations of Traditional Methods

- Conventional rule-based and signal processing methods are:
  - Sensitive to noise
  - Ineffective under varying load and fault conditions
  - Lacking real-time adaptability and scalability
- There is a growing demand for intelligent, data-driven solutions.

Literature Review

Ref	Model/Method Used	Remarks	Advantages	Drawbacks
[1]	ANN, SVM, Decision Trees(2023)	Highlights the importance of real-time monitoring to prevent large-scale power failures	Fast response time, adaptable to different fault types	Data quality dependency, poor generalization without proper training
[2]	Federated Learning with 1D-CNN-LSTM(2024)	Privacy-preserving hybrid deep model for smart grids	Privacy protection, scalable for large systems	High computational need, FL synchronization issues
[3]	Modified CNN(2020)	Detects faults during power swings with improved robustness	Enhanced detection accuracy, robust to transients	Large dataset need, misclassification in extreme conditions
[4]	Alienation Coefficient + SVM(2020)	Improves classification using unique waveform features	High accuracy, effective feature extraction	Less tested on real-world noisy data, SVM tuning required
[5]	CNN-based Deep Learning(2022)	Detects fault location in branching networks using voltage/current signals	High accuracy, reduces manual inspection	Needs large labeled data, computationally heavy
[6]	CNN, LSTM, ANN, SVM, RF, KNN, Naïve Bayes + DWT(2025)	Compares advanced ML models on simulated data	High classification accuracy, handles both feature/time series data	High training cost, trained only on simulations, real-time use needs adaptation
[7]	ANN, Multi-Layer Perceptron (MLP)(2022)	Detects, locates, classifies faults using current and voltage	Fast detection (within 20ms), effective under noise	Data quality sensitive, retraining needed for new configs
[8]	SVM, RF, DT, KNN, ANN(2023)	Comparative study of ML models	Helps identify best model for fault automation	Dependent on data quality, high compute for some models
[9]	Transformer-based DL(2024)	Uses attention mechanism for temporal patterns in faults	High accuracy, real-time detection, better generalization	Needs large training dataset, high computational cost
[10]	Hybrid XGBoost-LSTM(2024)	Cold weather fault prediction using hybrid model	Good feature selection, time-sequence capture	Data dependency, complex and compute-heavy
[11]	LSTM	Fault detection/classification for 6-phase lines(2024)	Handles large data, robust to parameter changes	Requires extensive simulation, sensitive to data quality
[12]	Deep Neural Network (DNN)(2022)	Classifies and locates faults with high precision	98.775% accuracy, 2% location error in 80% cases	Real-world complexity may affect performance, needs big dataset
[13]	Back Propagation Neural Network (BPNN)(2020)	Classifies faults in 220kV 3-phase line model	Fast training, adaptable to parameters	Algorithm sensitivity, slow convergence in some cases

Table.I

Problem Statement

- Traditional fault detection methods lack adaptability and accuracy in modern, dynamic power systems.
- They struggle with evolving fault patterns, class imbalance, and poor generalization.
- There is a need for a robust, interpretable deep learning model for real-time fault classification.
- This project addresses that gap using a lightweight and explainable Attention-LSTM framework.

Research gaps

- Most deep learning models lack interpretability for critical decision validation.
- Existing models struggle with imbalanced fault vs. non-fault data.
- High-performing models like Transformers require heavy computational resources.
- Temporal feature relevance is often underutilized in current architectures.

Objectives vs Accomplishments

S.no	Objectives	Status
1.	Design and implement an Attention-based LSTM model for fault classification	✅ Successfully completed
2.	Address class imbalance using label smoothing and dropout	✅ Implemented and effective
3.	Achieve high accuracy and generalization across multiple fault types	✅ Achieved 98.3% accuracy
4.	Ensure model interpretability using SHAP-based explainable AI	✅ SHAP integrated with insights
5.	Enable real-time interaction through a user-friendly dashboard	✅ Dashboard built

Table.2

Proposed Methodology

- Our model pipeline starts with multivariate time-series data comprising voltage and current readings.
- We feed this data into an LSTM layer that captures temporal dependencies, followed by a self-attention mechanism to weigh the most informative time steps.
- The output is passed through dense layers with dropout for regularization and ends in a softmax layer for multi-class classification.
- Label smoothing was also applied to improve generalization on imbalanced data.

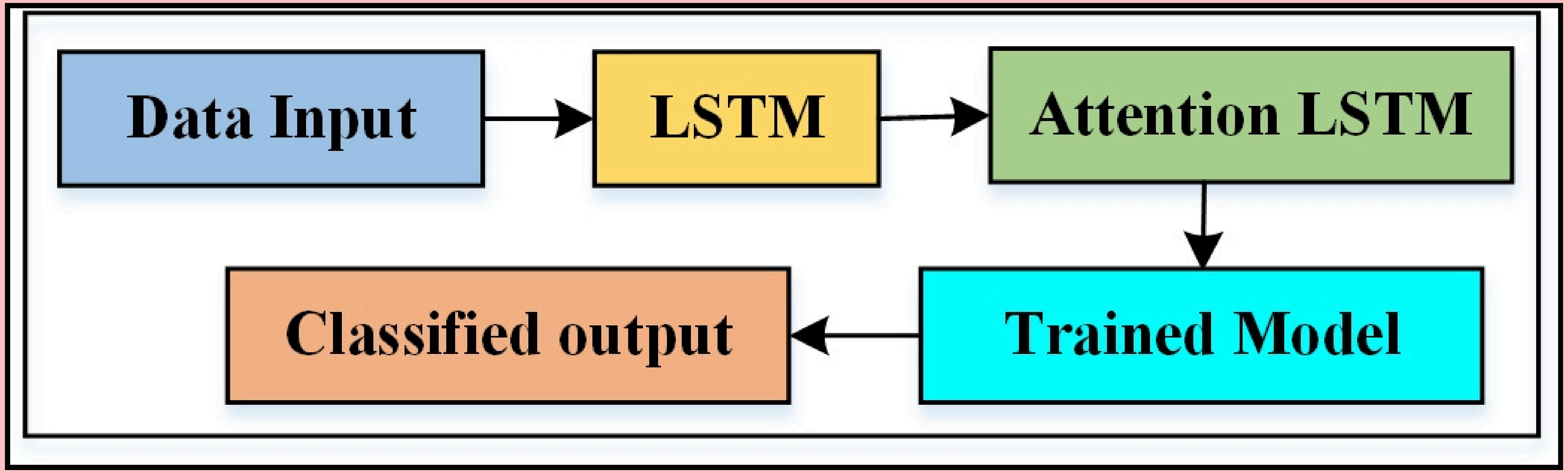

Fig.I

Model Architecture

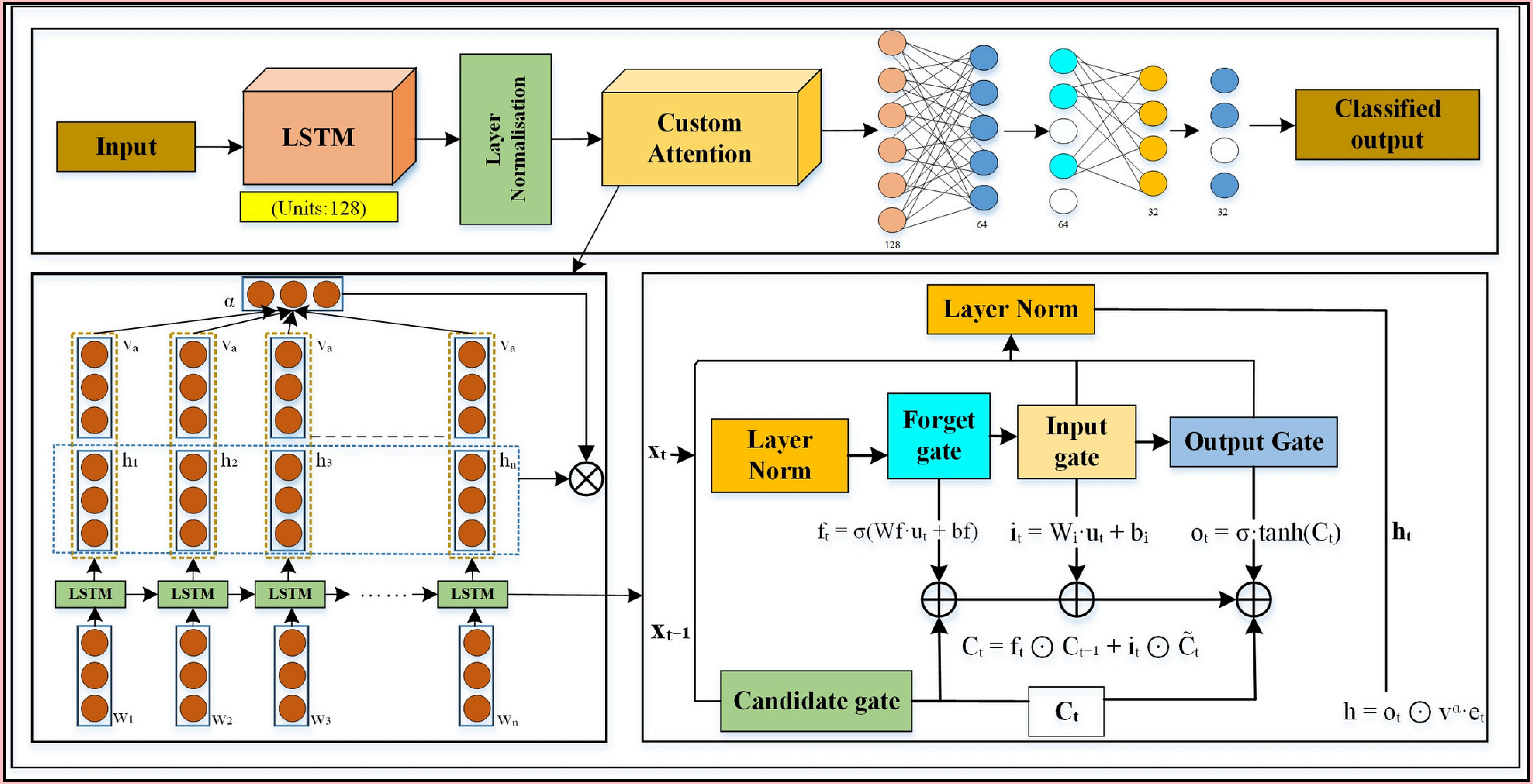

Fig.2

Results

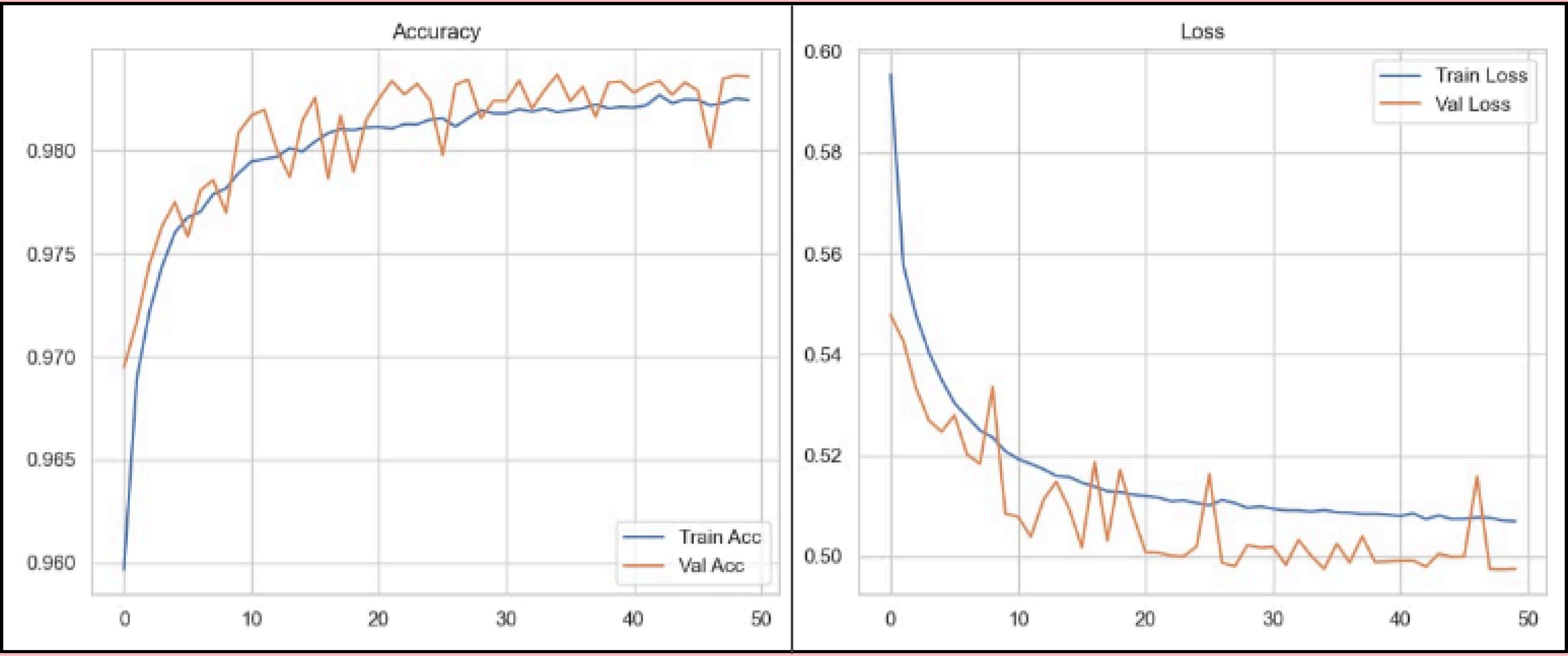

Fig.3

Results

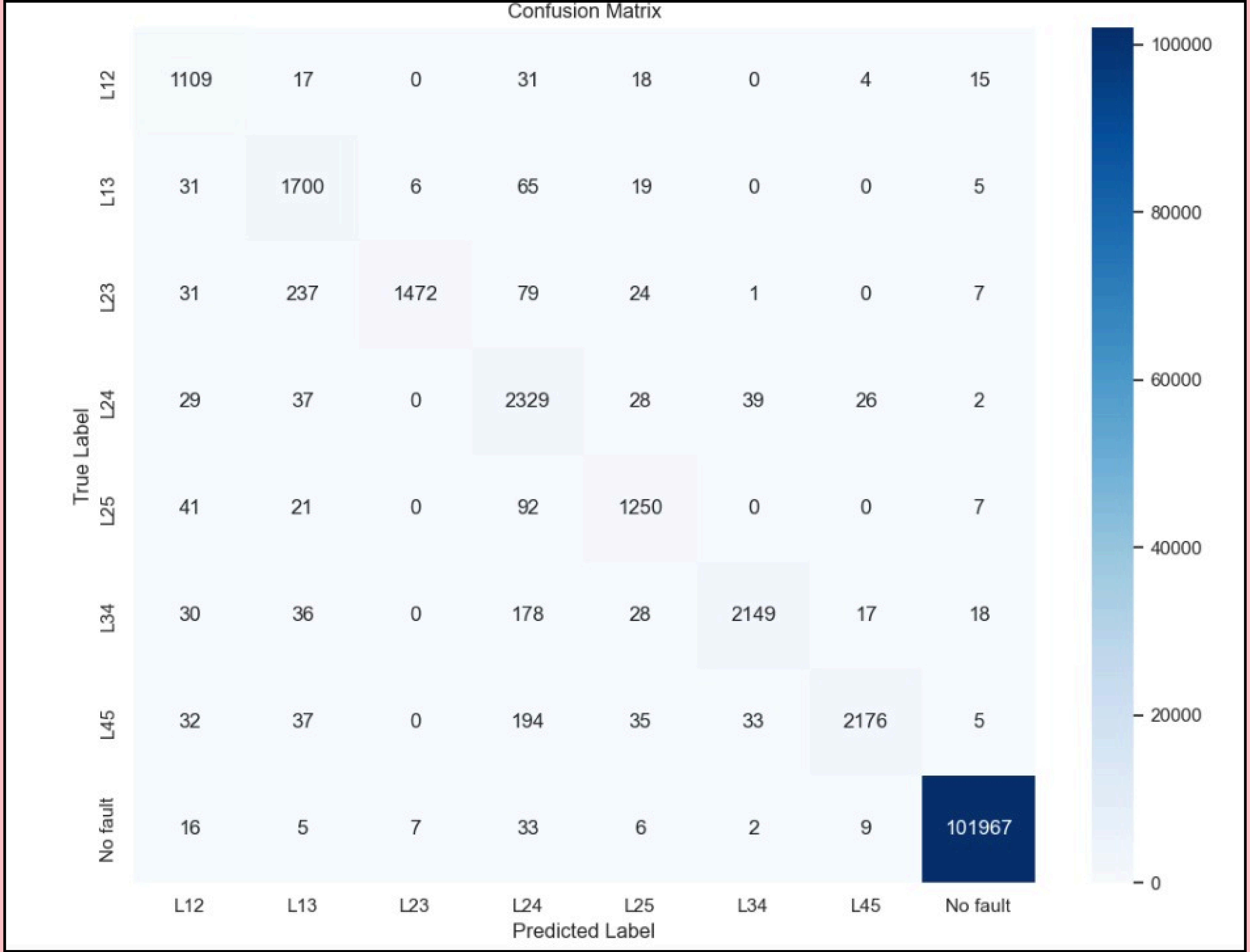

Fig.4

Results

Accuracy: 98.38%

Classification Report:

	precision	recall	f1-score	support
L12	0.81	0.80	0.81	5576
L13	0.87	0.88	0.88	9398
L23	0.99	0.81	0.89	9402
L24	0.74	0.91	0.82	12555
L25	0.86	0.86	0.86	7128
L34	0.92	0.90	0.91	12555
L45	0.97	0.87	0.92	12555
No fault	1.00	1.00	1.00	509754
accuracy			0.98	578923
macro avg	0.90	0.88	0.88	578923
weighted avg	0.99	0.98	0.98	578923

Fig.5

Results

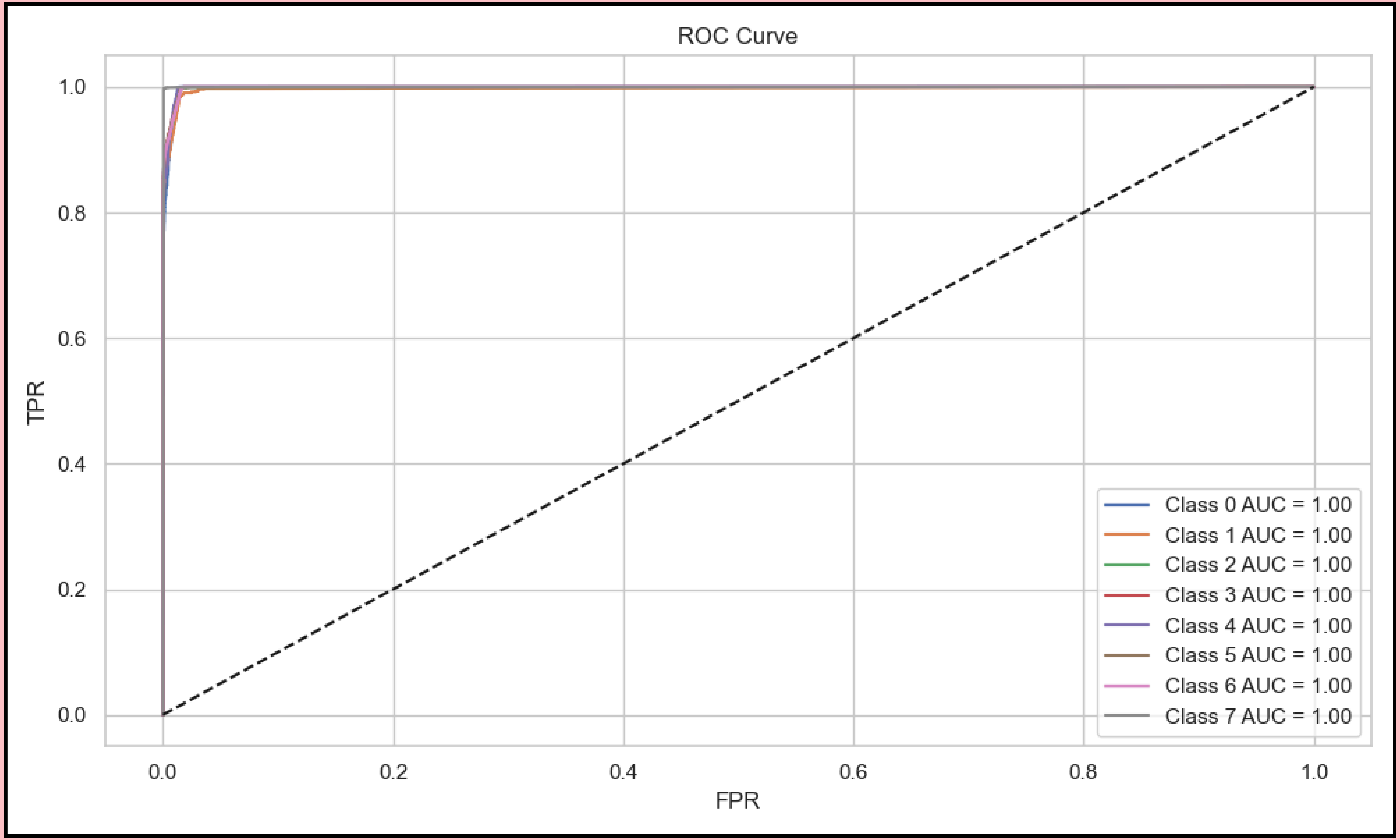

Fig.6

Explainable AI (SHAP)

- To ensure interpretability, we integrated SHAP (SHapley Additive Explanations).
- This figure shows SHAP values for the top 5 influential features per fault class.
- Features like Ia23I_{a23}Ia23 and Ia13I_{a13}Ia13 consistently contributed to fault predictions.
- SHAP allowed us to explain and validate model decisions, which is essential in safety-critical systems.

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==== SHAP Interpretation ====

Top 5 influential features for class 'L12':
1. Ia23: Importance = 0.0171, generally increases prediction
2. Ia13: Importance = 0.0061, generally decreases prediction
3. IaL12: Importance = 0.0044, generally decreases prediction
4. IbL12: Importance = 0.0031, generally decreases prediction
5. IcL12: Importance = 0.0027, generally decreases prediction

Top 5 influential features for class 'L13':
1. Ia23: Importance = 0.0173, generally increases prediction
2. Ia13: Importance = 0.0064, generally decreases prediction
3. IaL12: Importance = 0.0040, generally decreases prediction
4. IbL12: Importance = 0.0034, generally decreases prediction
5. Ib13: Importance = 0.0027, generally decreases prediction

Top 5 influential features for class 'L23':
1. Ia23: Importance = 0.0167, generally increases prediction
2. Ia13: Importance = 0.0070, generally decreases prediction
3. IaL12: Importance = 0.0043, generally decreases prediction
4. Ib13: Importance = 0.0031, generally decreases prediction
5. IbL12: Importance = 0.0029, generally decreases prediction

Top 5 influential features for class 'L24':
...
5. IbL12: Importance = 0.0030, generally decreases prediction
```

Fig.7

Comparison with other Models

Model	Accuracy (%)	Macro Precision	Macro Recall	Macro F1	Weighted Precision	Weighted Recall	Weighted F1
Attention-LSTM	**98.00**	**0.88**	**0.87**	**0.87**	**0.98**	**0.98**	**0.98**
CatBoost + Transformer	96.75	0.74	0.69	0.69	0.96	0.97	0.96
DBN + DNN	85.10	0.91	0.71	0.75	0.85	0.85	0.82
CNN-LSTM + CatBoost	87.43	0.92	0.87	0.86	0.92	0.87	0.86

Fig.8

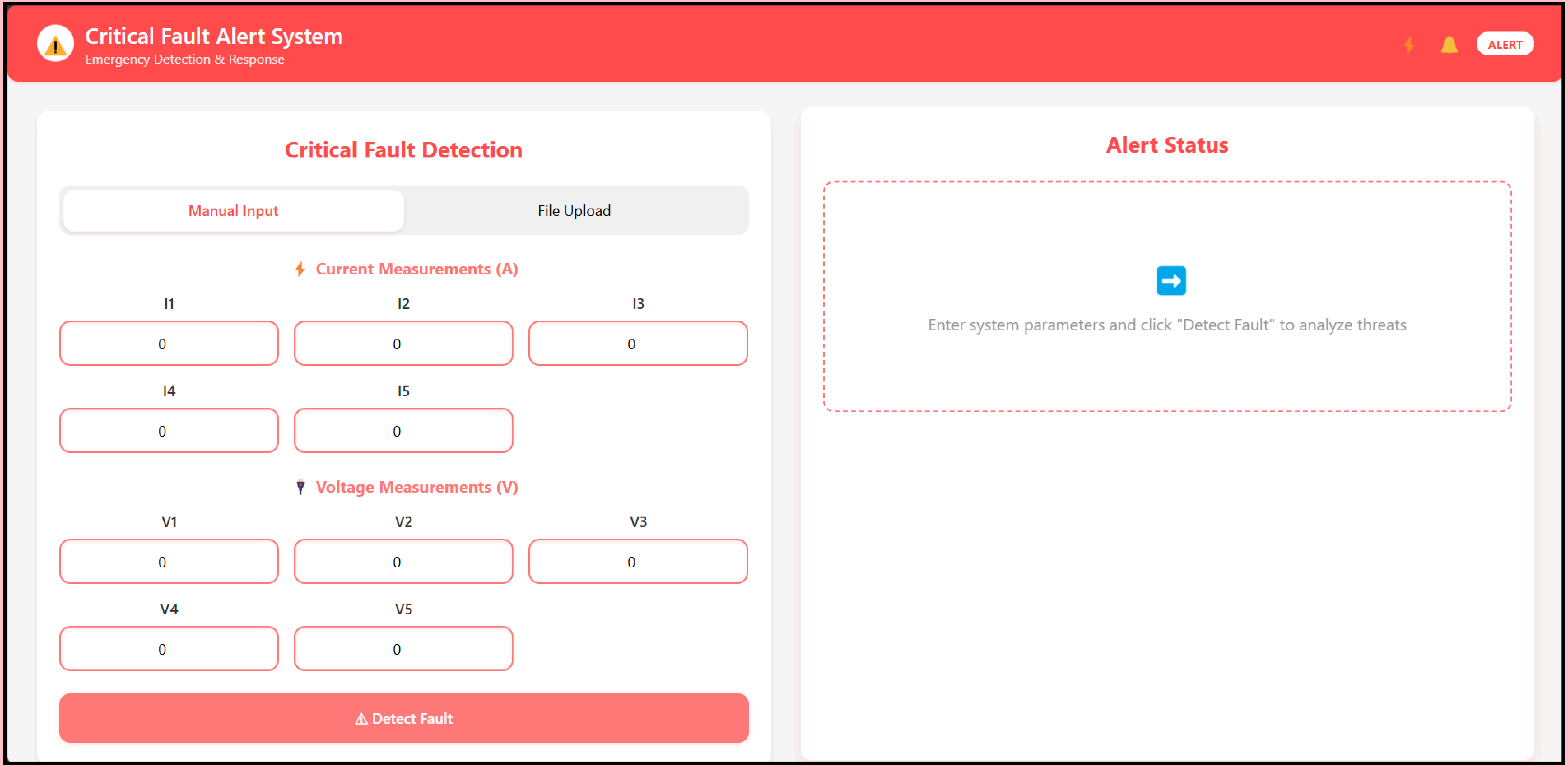

Fig.9

Dashboard

Future Scope

- Deploy the model on Edge TPU or FPGA for real-time hardware acceleration.
- Integrate weather and environmental data for multimodal fault prediction.
- Extend the model for fault location and severity estimation.
- Build a full-scale SCADA integration for live grid monitoring.
- Improve model robustness using adversarial training and uncertainty model

Conclusion

In conclusion, we have successfully met all our objectives.
Our Attention-LSTM model offers high fault classification accuracy, handles class imbalance, and provides interpretability via SHAP.
Its lightweight architecture makes it suitable for real-time fault detection in power transmission systems.

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Thank You!