Internship Summary Report

Intern Name: Amoggha C H
USN: 1MS21AI006
Branch: Artificial Intelligence and Machine Learning (AIML)
Mentor: Dr. A. Ajina
Organization: L&T Defence
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Introduction

During my internship at L&T Defence, I worked on three distinct tasks that explored advanced applications of deep learning in anomaly detection, object detection, and synthetic data generation. The projects were centered around building efficient models and pipelines tailored for time-series vibration data, PCB component detection, and side scan sonar image generation. Each task provided a unique challenge, requiring the implementation of different neural network architectures and data processing techniques.

Task 1: Anomaly Detection in Time-Series Vibration Data

Objective
To identify anomalies in vibration data from rotating machinery using various models, including an LSTM-based Autoencoder, aimed at detecting faults like bearing race faults, shaft misalignment, and rotor imbalance.

Dataset
Sourced from the Mendeley repository, the dataset consisted of time-series vibration signals under various load conditions, with both normal and faulty states, such as bearing inner and outer race faults.

Methods
Data Preprocessing:

- No missing values were detected.
- Detrending was applied to set the mean to 0.
- Features were standardized within the range of 0 to 1.

Models Used

Model	Accuracy
LSTM-based Autoencoder	93%
Ensemble Model	98%
One-Class SVM	99%
DBSCAN	100%
Kernel Density	28% (Best)
Isolation Forest	99%
KMeans	100%

Conclusion
The LSTM-based autoencoder demonstrated strong performance, achieving 93% accuracy. However, other models like DBSCAN and KMeans performed better with up to 100% accuracy. Future improvements should focus on real-time inference and model generalization.

Task 2: Custom Object Detection Using SSD Model

Objective

To detect and classify PCB components using a Single Shot Multibox Detector (SSD) model across two distinct datasets.

Environment

Details on hardware specifications and software configurations were not provided.

Performance Evaluation

Metric	1st Dataset	2nd Dataset
Total Inference Time	3.76 seconds	0.0973 seconds
Frames Per Second (FPS)	13.84	10.28
Mean Average Precision	16.53%	0.5921
Average Precision	0.7241	0.8699
Average Recall	0.3850	0.6602
Mean IoU	0.1536	0.3090

Key Findings

- The SSD model performed better on the 2nd dataset, achieving higher precision and a balanced F1 score.
- The 1st dataset exhibited lower recall and poor bounding box localization, resulting in a low Mean IoU.

Recommendations

- Improve recall and bounding box localization for better generalization.
- Experiment with different augmentations and model architectures to boost performance.

Conclusion

The SSD model showed promising results on the 2nd dataset but struggled with the 1st dataset. Future enhancements should focus on improving recall and localization accuracy.

Task 3: Synthetic Data Generation for Side Scan Sonar Datasets

Objective:
Develop a robust pipeline for generating synthetic side scan sonar images using diffusion models and autoencoders.

Datasets:

- **Dataset A:** IEEE Dataport
- **Dataset B:** Figshare
- **Dataset C:** Google Drive
- **Dataset D:** SeabedObjects (GitHub)

Methodologies:

- **Autoencoder Architecture:**
    - Implemented a convolutional autoencoder with LSTM enhancements.
    - Added Gaussian noise; trained using Mean Squared Error (MSE).
    - **Results:** Loss decreased from 0.1243 to 0.0066, but images lacked clear features.
- **Diffusion Model:**
    - Encoder-decoder setup with noise injection and gradual denoising.
    - Applied augmentations using the Albumentations library.
    - **Results:** Loss reduced from 0.0142 to 0.0066, but images were often blurred.

Challenges:

- Difficulty in preserving distinct sonar features.
- High-resolution (2048x2048) image generation was computationally intensive with minimal gains.

Recommendations:

- Explore UNet-based autoencoders or GANs for better feature preservation.
- Use domain-specific augmentations and perceptual metrics like SSIM.
- Conduct further experiments to improve feature retention.

Conclusion:
A strong foundation for synthetic sonar image generation was established, but further improvements are needed for better image clarity and feature preservation.

Overall Summary

Throughout the internship, I explored deep learning applications in anomaly detection, object detection, and synthetic data generation. Each project required different neural network architectures and tackled challenges related to dataset variability, model generalization, and computational efficiency. The LSTM-based autoencoder, SSD model, and diffusion techniques provided valuable insights into model performance, and the experience enhanced my understanding of advanced AI methodologies. Moving forward, I plan to refine these models and explore additional augmentations and evaluation metrics for improved robustness.

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