Project Report: Bearing Health Detection using Deep Learning and LLM

📊 Title:

Robust Bearing Health Classification using Spectrogram-Based CNN and LLM-Enhanced Knowledge Reasoning

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💡 Abstract

This project presents a comprehensive pipeline for **automatic bearing health classification** from vibration signals using deep learning. The approach converts raw vibration signals into spectrograms and trains a CNN to classify health conditions (Normal, IR, OR, Ball). To improve performance and robustness, adaptive **signal augmentations** were used: RMS-scaled Gaussian noise, amplitude scaling, and frequency masking. Further, a **retrieval-augmented generation (RAG) system with an LLM** was integrated to support real-time fault classification using vector-based reasoning. The final system offers high classification accuracy with scalable prediction support suitable for industrial deployment.

📚 Dataset and Preprocessing

- **Source**: CWRU (Case Western Reserve University) bearing dataset
- **Format**: `.mat` files, each containing raw vibration signals
- **Sampling Rate**: 12,000 Hz
- **Segmentation**: 5-second windows
- **Spectrogram Conversion**:
    - Shape: 128×128
    - Function: `scipy.signal.spectrogram`

- Spectrograms are computed using `nperseg=256`, `noverlap=128` and converted to log scale using `10 * log10(Sxx + 1e-8)`

🔄 Augmentation Techniques

1. RMS-Scaled Gaussian Noise

```
def add_rms_scaled_noise(signal, noise_ratio=0.2):
    rms = np.sqrt(np.mean(signal**2))
    noise = np.random.normal(0, noise_ratio * rms, size=signal.shape)
    return signal + noise
```

- Adds realistic noise relative to signal energy
- Prevents under/over-noising and supports generalization
- Ensures weak signals aren't overwhelmed and strong signals are realistically disturbed

2. Amplitude Scaling

```
def amplitude_scaling(signal, scale_range=(0.5, 1.5)):
    scale = np.random.uniform(*scale_range)
    return signal * scale
```

- Simulates signal variation due to physical load changes
- Creates synthetic samples with similar structure but varied intensities

3. Variable Frequency Masking

```
def frequency_masking(spec, num_masks=1, freq_masking_max_percentage=0.15):
    spec = spec.copy()
    num_freqs = spec.shape[0]
    for _ in range(num_masks):
        f = int(np.random.uniform(0.1, freq_masking_max_percentage) * num_freqs)
        f0 = np.random.randint(0, num_freqs - f)
        spec[f0:f0 + f, :] = 0
    return spec
```

- Randomly zeros out horizontal frequency bands
- Mimics missing sensor range or interference
- Forces CNN to rely on broader spectral features instead of fixed bands

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🧠 CNN Architecture

- **Input**: Spectrogram (128x128x1)
- **Layers**:
  - Conv2D (32, 64, 128) + BatchNorm + MaxPooling
  - Flatten + Dense (128) + Dropout (0.3)
  - Dense(4), softmax output
- **Loss**: Sparse Categorical Crossentropy
- **Optimizer**: Adam (lr = 0.0005)
- **EarlyStopping**: Patience = 5 to 15 depending on setup
- Designed to balance performance and trainability with relatively shallow depth

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🧠 LLM + Knowledge Base Integration (RAG-Based Fault Prediction)

To enable intelligent and scalable fault prediction, a **Retrieval-Augmented Generation (RAG)** architecture is implemented alongside the CNN model. This system integrates a **local LLM (LLaMA 3.2 via Ollama)** with a semantic knowledge base derived from labeled vibration signals.

🔧 Components:

- **LLM**: [Ollama]() running **LLaMA 3.2** locally.
- **Embeddings**: Generated using `SentenceTransformer` model: `all-MiniLM-L6-v2`.

- **Knowledge Base**: Descriptions of signal features and corresponding fault types (IR, OR, Ball, Normal), stored in a `.txt` file.
- **Vector Store**: FAISS (Facebook AI Similarity Search) is used to index and search the knowledge base embeddings efficiently.

🔍 **LLM Prediction Behavior:**

- Extracts features (RMS, kurtosis, skewness, peak-to-peak, crest factor, dominant frequency) from the input signal.
- Forms a query string from the features and embeds it using the same SentenceTransformer.
- Retrieves the top-k most semantically similar cases from the knowledge base via FAISS.
- Passes the retrieved cases along with extracted signal features as a prompt to the LLaMA 3.2 model.
- The LLM then **predicts the fault class (Normal, IR, OR, Ball)** based purely on semantic similarity with known cases.

🔬 Experimental Comparison

Experiment	Noise Type	Masking Type	Spectrogram Size	Epochs	Accuracy
EXP-1	RMS (0.2x)	Variable	128x128	49	**0.9869**
EXP-2	Fixed (0.08)	Fixed (100px)	128x128	60	0.9224
EXP-3	RMS (0.1x)	Variable	256x256	65	0.9400

Best performance came from **EXP-1** due to adaptive augmentation and efficient 128x128 spectrograms.

⚠️ Design Trade-offs and Insights

❌ Drawbacks of Using 256×256 Spectrograms

- **Increased Memory & Time**: Training takes longer, consumes more GPU.
- **Overfitting Risk**: More pixels, same data → model may memorize noise or background.
- **Diminishing Returns**: Accuracy does not improve significantly beyond 128×128.
- **Inference Cost**: Slower predictions in real-time scenarios.

❌ Problems with Standard Gaussian Noise (Fixed σ)

```
noisy = signal + np.random.normal(0, 0.08, size=signal.shape)
```

- Adds the same noise level regardless of signal strength.
- **Weak signals** become overpowered, causing false positives.
- **Strong signals** barely change, reducing augmentation effectiveness.
- Inconsistent behavior across samples → unstable learning signal.

✅ How RMS-Scaled Noise Solves It

```
def add_rms_scaled_noise(signal, noise_ratio=0.2):
    rms = np.sqrt(np.mean(signal**2))
    noise = np.random.normal(0, noise_ratio * rms, size=signal.shape)
    return signal + noise
```

- **Signal-aware**: More noise for high-RMS signals; less for low-RMS
- **Realistic**: Matches real-world vibration sensor noise behavior
- **Balanced augmentation**: Every sample is augmented to the right extent
- **Robust model behavior**: Improves generalization on noisy/real-world data

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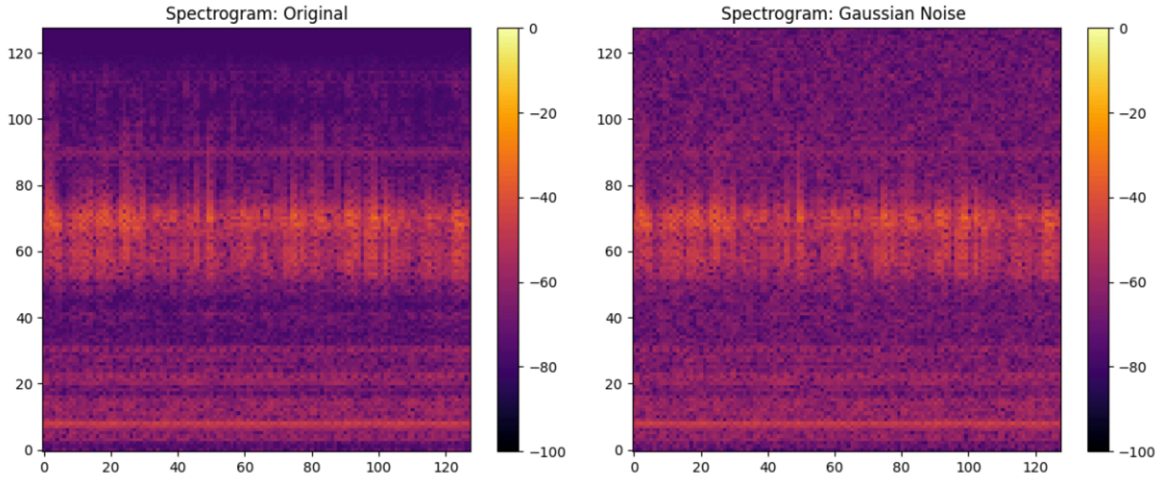
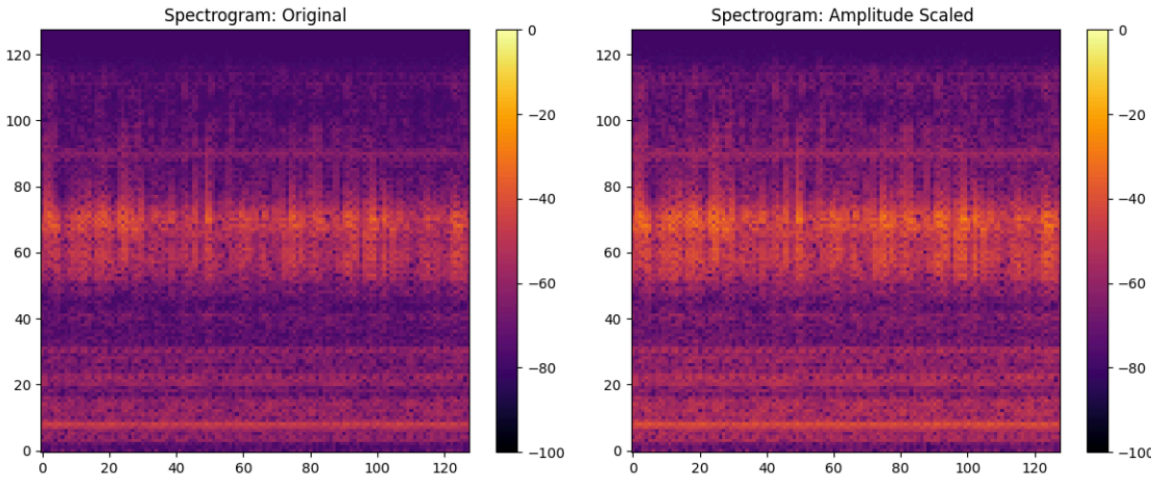
📊 Visual Results

Spectrogram Comparison

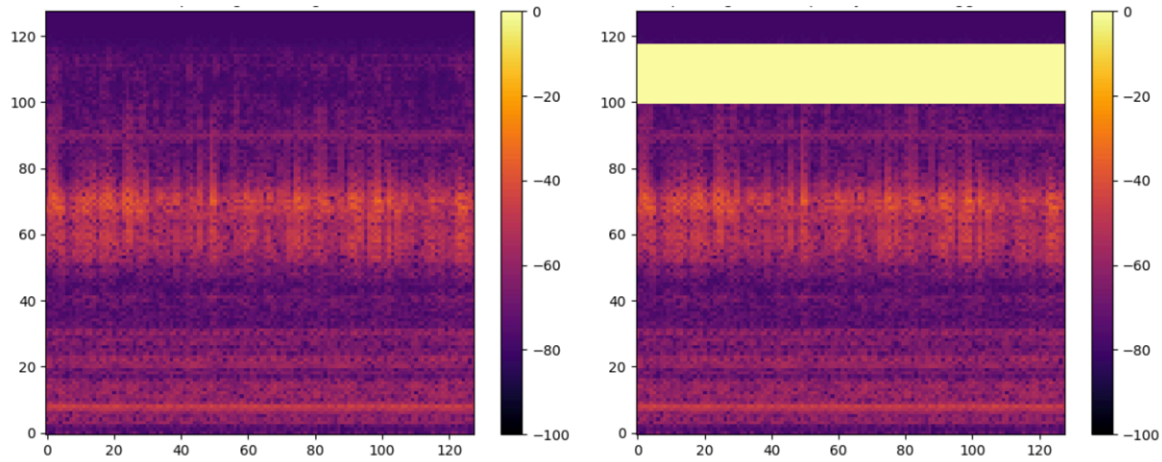
- Original vs Gaussian Noise



- Original vs Amplitude Scaling

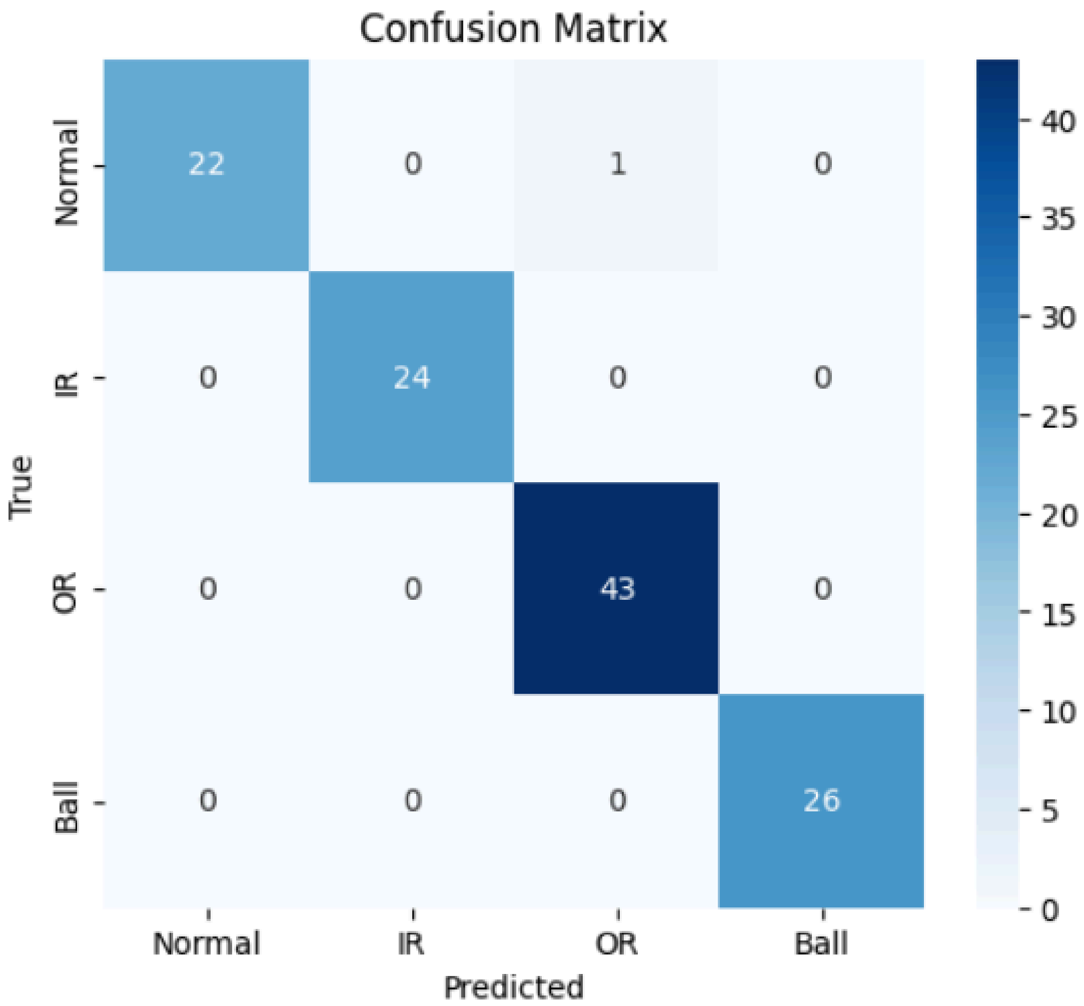


- Original vs Frequency Masking

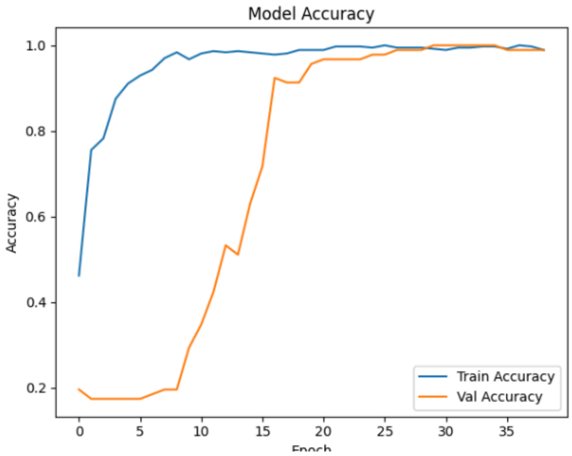


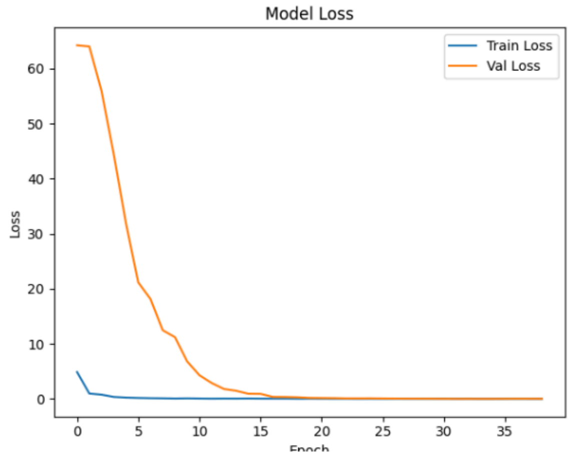
CNN Performance

- Confusion Matrix (EXP-1)

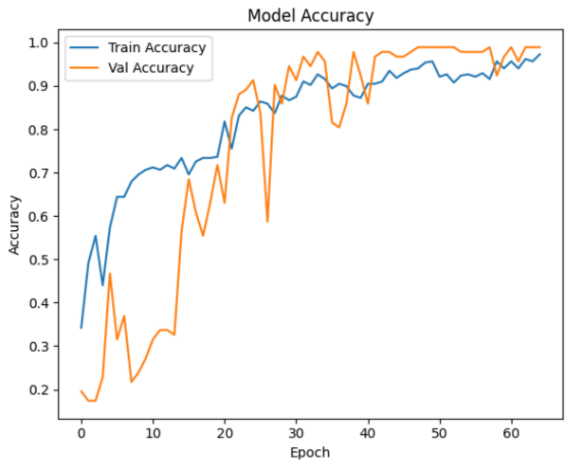


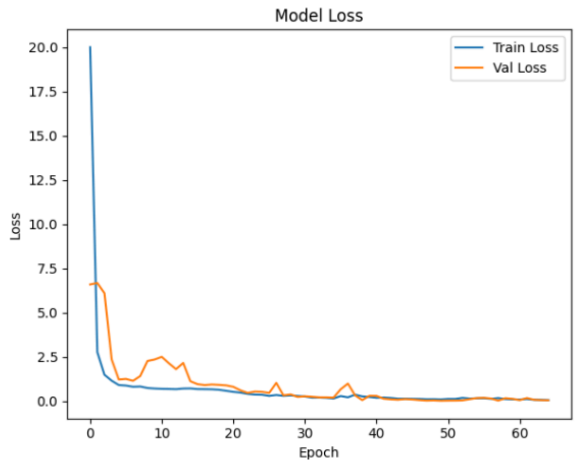
- Training Accuracy & Loss Curves



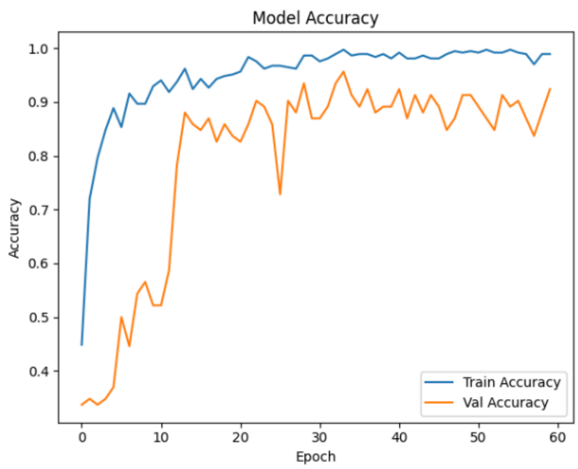


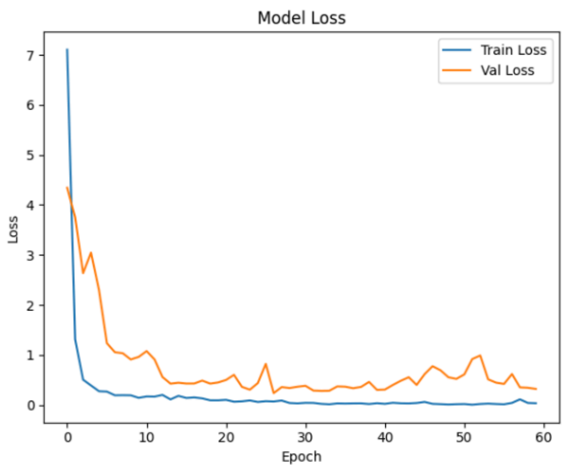
Using spectogram size as 256*256

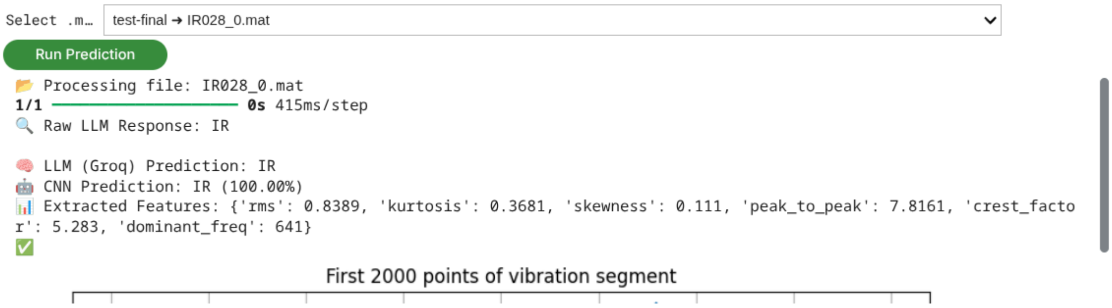




Using fixed masking







🧠 Insights

- **RMS-based augmentations** improved robustness
- **Variable frequency masking** simulated sensor unpredictability
- **128x128 spectrograms** balanced speed and resolution
- **LLM integration** enabled fault prediction via semantic retrieval of similar cases, improving interpretability of classification under noisy conditions

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📝 Conclusion

This project demonstrates that combining **signal-aware data augmentation** with **spectrogram-based CNNs** and a **lightweight LLM-based retrieval system** yields a highly effective and deployable solution for real-time bearing health classification.

The best model (EXP-1) achieved **98.69% accuracy** with only 49 epochs, outperforming other configurations with lower compute cost. The LLM system supported auxiliary predictions using embedded vector matching, making this framework not only accurate but also scalable across real-world industrial settings.

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