Results and Discussion

CNN outperforms RNN and LSTM with 82% accuracy. CNN recognizes frequent classes like 'Macarons'. Tables and confusion matrices highlight class-wise precision and recall.

Key Performance Results and Model Accuracy Comparison

CNN: 82% accuracy (highest performance)

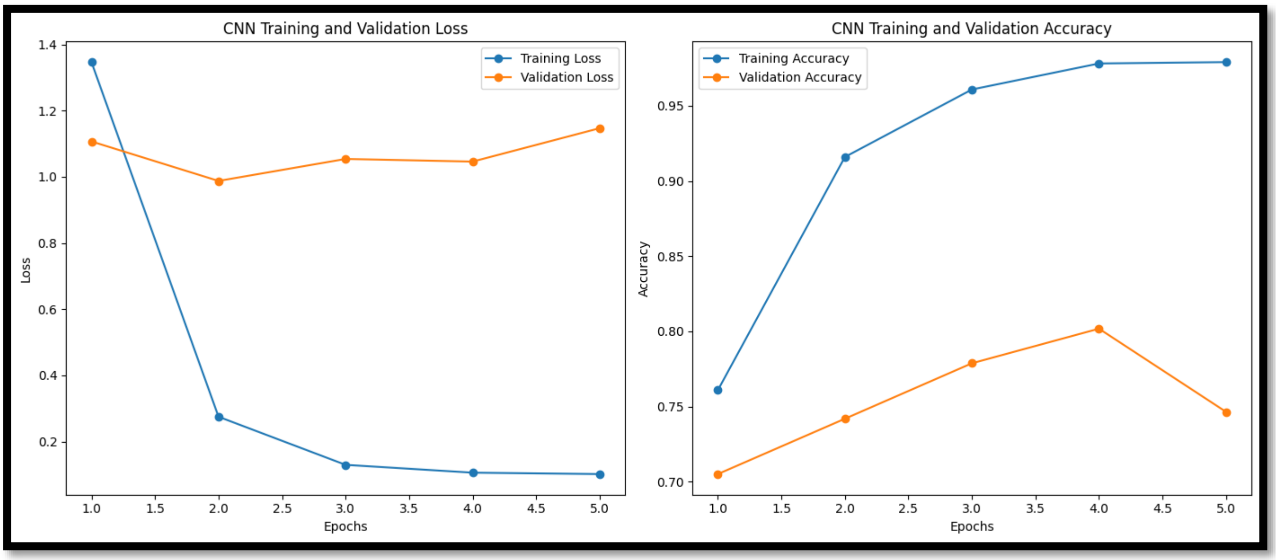

Figure 1 CNN performance

RNN: 58% accuracy

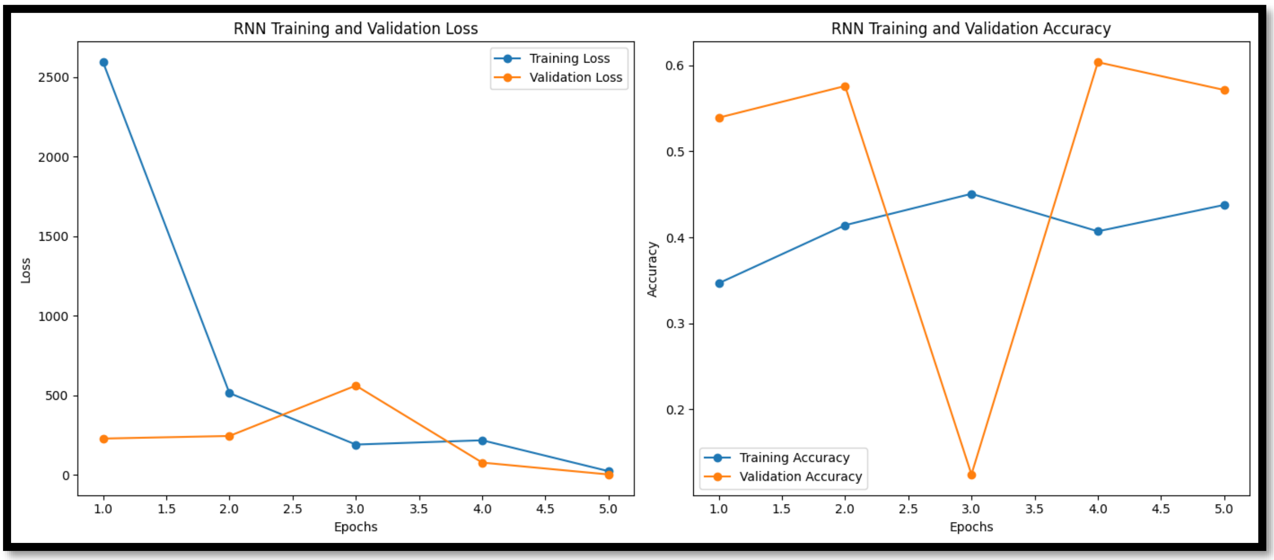

Figure 2 RNN Performance

LSTM: 58% accuracy

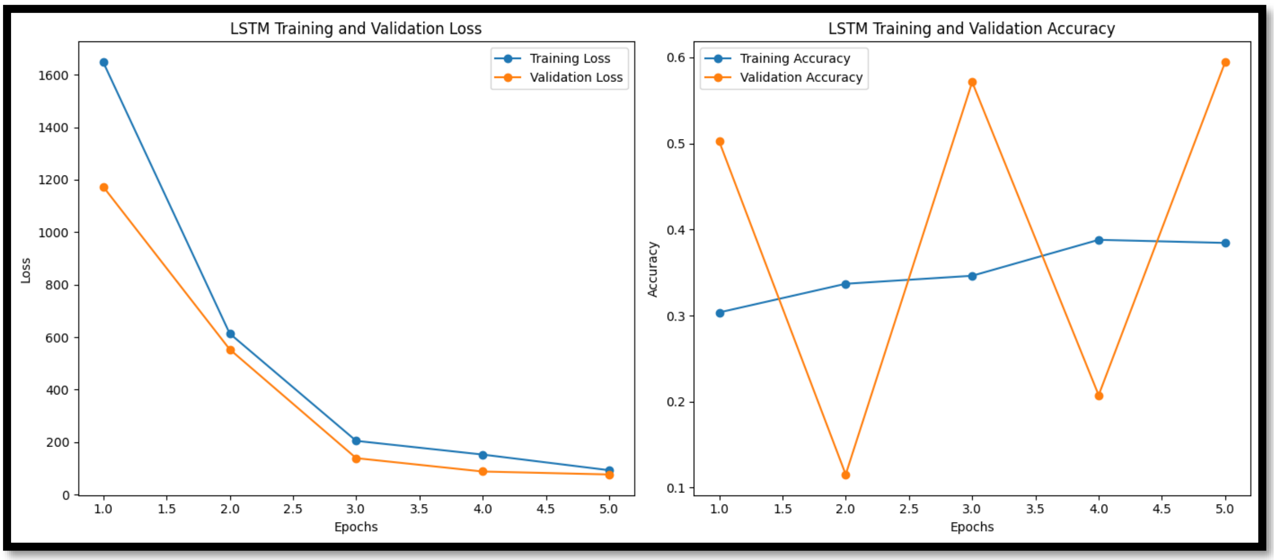

Figure 3 LSTM performance

CNN Performance Analysis

- **Strengths**: Effective spatial feature extraction for image classification
- **Transfer Learning**: VGG16 pre-trained weights improved performance
- **Alignment**: Results match literature (Farinella et al. 2021: 85% accuracy)

Key Findings

CNN Advantages

- Superior spatial hierarchy capture for food identification
- Transfer learning reduced training time and improved accuracy
- Best suited for complex visual data classification

Model Limitations

- **Data Imbalance**: Poor performance on rare classes (Choco, Mint macaron flavors)
- **Zero Accuracy**: Some classes had 0% precision, recall, and F1-scores
- **RNN/LSTM Issues**: Sequential models less effective for spatial image features

Performance Metrics

- **CNN**: Unweighted mean precision/recall/F1-score: 0.38-0.41
- **Problem Classes**: Cheesecake, Pizza, Tiramisu showed poor recognition

- **Root Cause**: Imbalanced dataset affecting overall performance

Literature Comparison

- **Bu, Hu, Zhang (2024)**: 92% with transfer learning + ensemble
- **Mansouri et al. (2023)**: 90% with CNN-SVM hybrid
- **Bolaños & Radeva (2016)**: Emphasized dataset balance importance

Practical Applications

- **Mobile App**: Real-time nutritional assessment and portion size feedback
- **Health Monitoring**: Dietary assessment integration
- **Implementation**: Successfully bridged research to practical application

Future Recommendations

1. **Address Data Imbalance**: Use data augmentation and oversampling
2. **Hybrid Models**: Combine CNN strengths with RNN/LSTM for sequential data
3. **Dataset Expansion**: Include diverse cultural foods for better generalization
4. **Advanced Techniques**: Explore CNN-SVM combinations for improved accuracy

Conclusion and Achievement

CNN with transfer learning is superior for food image recognition. Achieved successful model training, classification, and interpretation.

Project Achievements

Main Objective

Successfully developed and analyzed three neural network models (CNN, RNN, LSTM) for food image classification.

Model Performance Results

CNN Model

- **Accuracy**: 82% (best performance)
- **Architecture**: Pre-trained VGG16
- **Strengths**: Excellent visual feature handling, high precision/recall for 'Macarons'
- **Limitations**: Struggled with under-represented classes (Macarons-Choco, Macarons-Mint)

RNN Model

- **Accuracy**: 58%
- **Purpose**: Sequential dependency capture
- **Limitations**: Poor performance on classes with few samples
- **Insight**: Revealed challenges of applying RNNs to image classification where temporal dependencies are less critical

LSTM Model

- **Accuracy**: 58%
- **Focus**: Long-term dependency representation
- **Issues**: Similar precision/recall problems as RNN for sparse classes
- **Potential**: Showed promise for 'Macarons' classification in specific contexts

Key Conclusions

1. **CNN Superior**: CNNs significantly outperform RNNs/LSTMs for image classification tasks

2. **Visual Features**: Spatial feature extraction more important than sequential processing for food recognition
3. **Data Imbalance**: Under-represented classes remain a major challenge across all models
4. **Objective Met**: Successfully implemented, trained, and evaluated all three neural network architectures
5. **Practical Insights**: Demonstrated strengths and limitations of each approach for food image classification