Classification Using Doppler Dataset

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***Abstract*—This project focuses on detecting and classifying Doppler radar data into drones, cars, and people by leveraging Convolutional Neural Networks (CNNs). With the growing use of drones in various industries, having reliable detection systems is becoming crucial. We conduct classification using advanced CNN models, specifically MobileNet V2 and GoogLeNet, to compare their performance against each other through the implementation of transfer learning.**

***Index Terms*—Doppler Radar, Classification, CNN, MobileNet V2, GoogLeNet, Transfer Learning, Deep Learning**

I. Introduction

The integration of Doppler radar with CNNs for detecting and classifying drones, cars, and people has become increasingly useful in fields such as security, surveillance, traffic monitoring, and autonomous vehicles. This project uses CNNs to perform classification tasks using Doppler radar data. By leveraging CNN models, including MobileNet V2 and GoogLeNet, we aim to explore transfer learning and improve the accuracy of radar-based classification systems, enhancing our understanding of deep learning techniques through real-time implementation.

In recent years, the rapid development of radar technology and deep learning has opened up new possibilities for intelligent classification and recognition systems. Doppler radar, with its ability to capture motion and velocity information, provides a unique dataset that complements conventional image or video data. Integrating Doppler radar data with CNNs enables the classification of objects based on their movement patterns and physical characteristics, overcoming limitations faced by optical systems in poor visibility conditions such as fog, darkness, or glare. This fusion of radar technology and CNNs has significant applications in critical areas such as drone detection for airspace management, pedestrian recognition for advanced driver-assistance systems (ADAS), and vehicle classification for traffic optimization. The project seeks to combine the feature extraction capabilities of CNNs with the robustness of radar data to develop a system that is both efficient and adaptable, leveraging the strengths of models like MobileNet V2 and GoogLeNet to ensure scalability and performance in real-world scenarios.

II. Related Work

Key research in Doppler radar-based detection using CNNs has led to significant advancements in object detection. Projects such as RadarNet and DeepRadar have successfully used CNNs for classifying radar signals and detecting objects like vehicles and pedestrians, especially in autonomous vehicle applications. Additionally, studies on radar-based drone detection have utilized deep learning to identify drones through radar data, enhancing security and surveillance. Research combining LiDAR and radar has further improved vehicle detection accuracy by integrating the motion-detection power of radar with LiDAR's high-resolution spatial data. Collectively, these efforts demonstrate the potential of integrating radar signal processing with deep learning for more efficient real-world object detection systems.

Further exploration into radar-based detection systems has highlighted the unique advantages of combining radar technology with deep learning. Unlike traditional optical sensors, Doppler radar excels in capturing motion and velocity information, making it especially effective in scenarios with poor visibility, such as fog, darkness, or heavy rain. Advanced deep learning architectures, such as CNNs, have demonstrated remarkable capabilities in extracting meaningful features from radar spectrograms and micro-Doppler signatures, enabling accurate classification and detection of various objects. For example, systems like RadarNet and DeepRadar utilize multi-layered CNN frameworks to process radar signals in complex environments, effectively distinguishing between objects with similar velocity profiles but different shapes or behaviors. Radar-based drone detection systems also employ CNNs to analyze time-frequency representations of radar signals, identifying the unique flight patterns of drones even amidst challenging background noise or clutter.

In addition to standalone radar-based systems, hybrid detection frameworks that integrate LiDAR and radar data have shown significant promise in improving object detection accuracy. By combining radar's strength in motion detection with LiDAR's high-resolution spatial data, these systems achieve greater robustness and precision, particularly in applications like autonomous vehicles and advanced surveillance. For instance, hybrid approaches enhance the detection of vehicles and pedestrians by fusing the complementary data streams, overcoming limitations that each sensor technology might face independently. Such advancements underscore the growing potential of integrating radar signal processing with deep learning to create more reliable and efficient detection systems across diverse real-world scenarios.

III. Methodology

A. Novel CNN Model

The methodology involves designing a custom Convolutional Neural Network (CNN) to classify Doppler radar data. The dataset is first preprocessed and split into training, validation, and test sets. Specifically, the data is divided into 70% for training 20% for testing, and 10% for validation, ensuring a balanced approach to model training and evaluation. The custom CNN architecture is built to handle the specific input shape of the radar data (11, 61, 1) and consists of three convolutional blocks. Each block includes a convolutional layer with ReLU activation, batch normalization for stabilizing and accelerating training, and max pooling layers for dimensionality reduction while preserving critical features. The third block omits max pooling to retain more spatial information before flattening the feature maps. This multi-stage feature extraction process is designed to learn and capture hierarchical features relevant to radar data classification.

After feature extraction, the network transitions to fully connected layers, where two dense layers with 128 and 64 units are used for high-level representation learning. Dropout regularization is applied to these layers with rates of 0.5 and 0.3 to prevent overfitting, and an L2 kernel regularizer further ensures generalization by penalizing large weights. The final layer is a dense layer with three units and a softmax activation function, outputting probabilities for the three target classes. The model is compiled with categorical cross-entropy loss and the Adam optimizer for efficient learning. Training includes early stopping based on validation loss to prevent overfitting and automatically restore the best weights. This custom CNN balances complexity and regularization to effectively learn from the radar dataset, with a careful train-test-validation split to ensure robust model evaluation and achieve high classification accuracy. The model is trained for 50 epochs. We have kept the patience value to 12 which is why our model ran for 17 epochs.

Fig. 1. Model Architecture

B. MobileNet V2

The methodology involves utilizing a pre-trained MobileNetV2 model to classify Doppler radar data by adapting it for a custom input shape. MobileNetV2, known for its efficiency and performance in feature extraction, is loaded without the top layers to act as a feature extractor. The dataset is first preprocessed and split into training, validation, and test sets. The data is divided into 70% for training 20% for testing, and 10% for validation sets. Since Doppler radar data has a distinct input shape (11, 61, 1), a custom preprocessing layer is implemented using a Lambda function. This layer resizes the radar data to the expected input dimensions of MobileNetV2 (224, 224, 3) and tiles the single-channel data across three channels. By freezing the weights of the pre-trained base model, the transfer learning approach leverages knowledge from the ImageNet dataset while avoiding overfitting to the smaller radar dataset.

The classification head of the model consists of a global average pooling layer to reduce feature dimensionality, followed by a dropout layer of rate 0.2 for regularization, and a dense layer with a softmax activation for multi-class classification. The model is compiled with the Adam optimizer and categorical cross-entropy loss, suitable for one-hot encoded labels, ensuring effective learning during training. The model is trained for 50 epochs, with accuracy monitored as a metric to evaluate its performance. This methodology balances the use of pre-trained features with custom adaptations for radar data, aiming to achieve high accuracy in a computationally efficient manner.

C. GoogLeNet (Inception V3)

The methodology centers around adapting the pre-trained InceptionV3 model for Doppler radar data classification using transfer learning. InceptionV3, known for its deep architecture and multi-scale feature extraction capabilities, is initialized without the top layers to act as a feature extractor, leveraging weights pre-trained on the ImageNet dataset. The dataset is first preprocessed and split into training, validation, and test sets. The data is divided into 70% for training 20% for testing, and 10% for validation sets. The model is designed to process radar data with an input shape of (11, 61, 1). To match InceptionV3's input requirements of (299, 299, 3), a custom Lambda layer resizes the radar data to the appropriate spatial dimensions and tiles the single-channel input across three channels to create a three-channel image. This preprocessing ensures the radar data aligns with the pre-trained model's input expectations while retaining its essential features. The base model's weights are frozen to retain the learned features from ImageNet, thus focusing the training on fine-tuning the classification head for radar-specific tasks.

The classification head includes a global average pooling layer to condense the feature maps into a compact vector, a dropout layer with a rate of 0.2 for regularization, and a dense layer with a softmax activation for three-class classification. The model is compiled using the Adam optimizer and categorical cross-entropy loss, which is appropriate for multi-class classification tasks with one-hot encoded labels. Accuracy is monitored as the primary metric to evaluate performance during training.The model is trained for 50 epochs, allowing it to learn patterns in the radar data while ensuring stability and avoiding overfitting through dropout and frozen base layers. This approach demonstrates a robust adaptation of a state-of-the-art model for radar data classification, balancing computational efficiency with high classification performance.

IV. Experimental Results

The accuracy of the novel CNN model was 94.94%. MobileNet V2 achieved 84.81%, while GoogLeNet (Inception V3) achieved 88.23%. The novel CNN model outperformed the others because it directly processes radar data in its raw form (11x61x1), whereas MobileNet V2 and GoogLeNet models resize the input to fit the model's dimensions. Another reason could be the nature of the data on which these SOTA models were trained being different from our scenario. This difference in data modularity and pre-training context played a significant role in achieving higher accuracy, indicating that transfer learning may not always be optimal when data modularity is crucial for classification.

Model	Precision	Recall	F1 Score
Novel CNN	0.952	0.951	0.95109
MobileNet V2	0.846	0.8427	0.84406
Inception V3	0.893	0.885	0.8862

TABLE I
Performance comparison of different CNN models

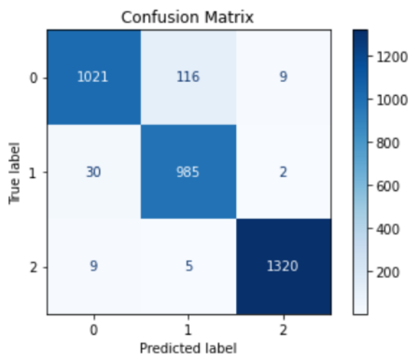

Fig. 2. Confusion Matrix for Novel Model

V. Conclusion and Future Work

This work sets the foundation for further improvements in radar-based object classification and transfer learning,

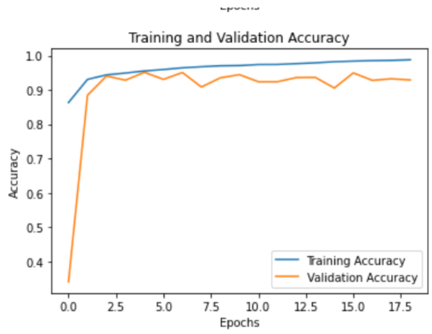

Fig. 3. Accuracy plot for Novel CNN Model

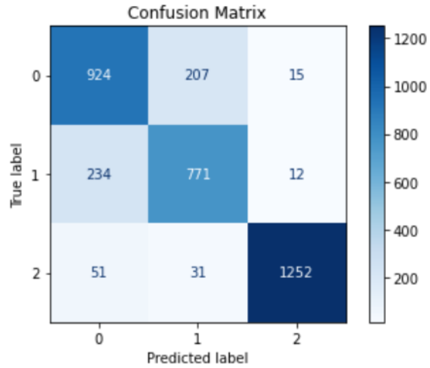

Fig. 4. Confusion Matrix for MobileNet V2 Model

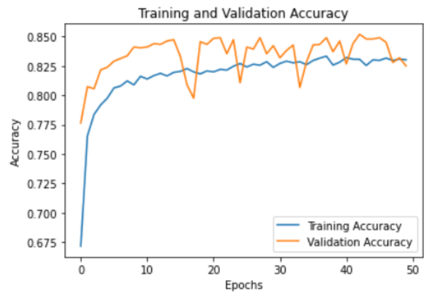

Fig. 5. Accuracy plot for MobileNetV2 Model

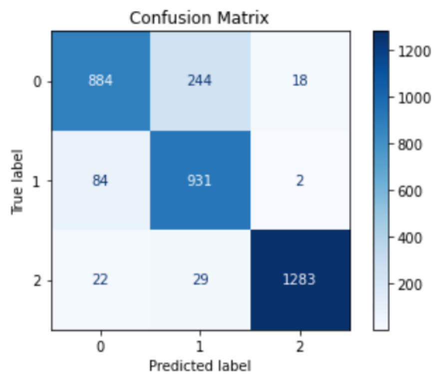

Fig. 6. Confusion Matrix for Inception V3 Model

Fig. 7. Accuracy plot for Inception V3 Model

with the goal of developing efficient systems for real-time, real-world applications. Future work could focus on improving generalization, computational efficiency, and adaptability to new datasets. Potential improvements include:

CNN Model for Doppler Radar Data

- **Data Augmentation:** Experimenting with techniques like rotation, scaling, and noise addition.
- **Model Optimization:** Hyperparameter tuning and advanced regularization.
- **Real-Time Processing:** Implementing the model on edge devices.

MobileNetV2-Based Model

- **Fine-Tuning:** Unfreezing and fine-tuning layers.
- **Without Reshaping:** Performing classification using original input dimensions.
- **Input Resizing:** Experimenting with lower input resolutions.
- **Lightweight Variants:** Exploring newer versions like MobileNetV3.

InceptionV3-Based Model

- **Multi-Scale Feature Extraction:** Adding custom modules.
- **Dynamic Input Resizing:** Adaptive resizing or alternative preprocessing.

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Appendix

The authors have contributed to this work as follows:

- **Shubhi Yadav**: Methodology, Visualization, Writing
- **Anant Terkar**: Conceptualization, Investigation

The authors confirm that all listed contributions adhere to the Contributor Roles Taxonomy (CRediT) guidelines.