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OPTIMIZING CNN ARCHITECTURES FOR DOPPLER RADAR VELOCITY ESTIMATION

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ABSTRACT

This report details our work on optimizing convolutional neural network (CNN) architectures for radial velocity estimation using Doppler radar data [1, 2]. Starting from a baseline model, we designed and evaluated six alternative architectures to improve prediction accuracy and computational efficiency. Despite constraints on model complexity, our best-performing architecture, DilateNetGAP, achieved a favorable balance between the test-RMSE and the parameter count [3, 4]. We also highlight challenges, including limited computational resources and strict design constraints, and propose directions for future improvements. Statistical evaluation and insights into model trade-offs are discussed to ensure the rigor of our findings [5, 6].

Index Terms— Doppler Radar, CNN Optimization, Dilated Convolutions, Velocity Estimation, Deep Learning

1. INTRODUCTION

Doppler radar technology measures the velocity of moving objects by analyzing the frequency shift of radar waves caused by motion. This principle is mathematically described by the Doppler equation [1]:

$$v_r = \frac{f_d}{2f_0}c, \tag{1}$$

where v_r is the radial velocity, f_d is the Doppler frequency shift, f_0 is the transmitted frequency, and c is the speed of light.

The task in this project was to predict the initial radial velocity of a golf ball after impact using Doppler radar spectrogram data [2]. The spectrogram stacks serve as input features, and the target radial velocity ranges between $[0, -50]$ m/s. Spectrogram-based models have proven effective for capturing spatial and temporal features in similar applications [7].

This report explores efficient CNN architectures for reducing RMSE and inference time while analyzing the trade-offs between model complexity and performance.

2. DATA

2.1. Dataset Description

The dataset comprises spectrogram stacks $\mathbf{S} \in R^{6\times74\times918}$, where six channels represent power and phase spectrograms corresponding to three radar polarizations. These spectrograms serve as input, and the target variable is the radial velocity $v \in [0, -50]$ m/s, representing post-impact velocity [2].

2.2. Preprocessing

To ensure consistency, power spectrograms were normalized to the range $[0, 1]$, while phase spectrograms were normalized to $[-\pi, \pi]$ [7]. Resizing was performed using bilinear interpolation to standardize the input dimensions to 74×918.

2.3. Dataset Splits

The dataset was divided into three subsets: the training set contained 1,234 samples, the validation set had 83 samples, and the test set included 739 samples. These splits ensured a rigorous evaluation of model generalization while adhering to established deep learning practices [6].

3. MODEL ARCHITECTURE

We experimented with six models, focusing on balancing accuracy, inference time, and parameter efficiency. Two representative models are presented: the **Base Model** and its optimized version, **DilateNetGAP**.

3.1. Base Model

The Base Model comprises standard 5×5 and 3×3 convolutions with ReLU activations, followed by 2×2 max pooling layers for spatial reduction. The output feature maps are flattened and passed through fully connected layers $\text{FC}(1024) \rightarrow \text{FC}(256) \rightarrow \text{FC}(1)$ for velocity prediction [6].

3.2. DilateNetGAP

DilateNetGAP improves upon the Base Model by incorporating dilated convolutions to enhance receptive field coverage [4]. Global Average Pooling (GAP) replaces Flatten operations to reduce parameters efficiently [3]. The fully connected layers are optimized to $\mathrm{FC}(512) \to \mathrm{FC}(128) \to \mathrm{FC}(1)$, further minimizing parameter count.

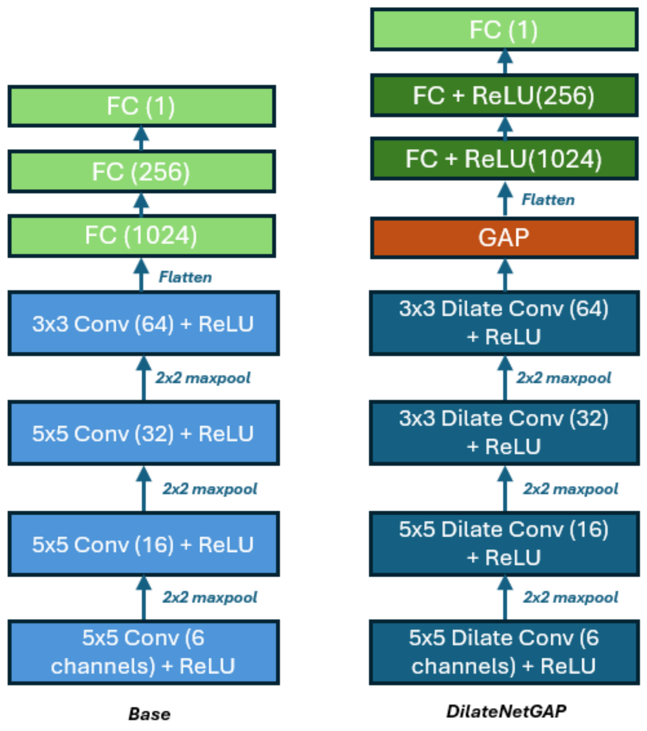

Fig. 1. Architectures of the Base Model and DilateNetGAP.

4. METHODOLOGY

Our approach followed an iterative and systematic process, starting with the provided baseline model, which achieved a test RMSE of **1.56** with approximately **38.4 million parameters**. The methodology was refined across three generations, culminating in the design of an optimized architecture.

4.1. Generation 1: Baseline Exploration

The first phase began with the baseline architecture, where small yet impactful modifications were introduced. Adjustments were made to activation functions, kernel sizes, and pooling strategies to observe their effects on performance. For example, ReLU activations were tested alongside other nonlinear activations to study gradient behavior [6]. Each experiment was trained for a limited number of epochs to quickly identify trends and isolate promising configurations for further evaluation. The experiments emphasized speed and insight over prolonged training.

4.2. Generation 2: Model Specialization

Based on the insights gained from Generation 1, three specialized models were developed to incorporate advanced architectural components. The first, **SiLUNet**, replaced traditional activation functions with the SiLU activation function to improve gradient flow and non-linearity [6]. The second, **DilateNet**, introduced dilated convolutions, expanding the receptive field without increasing computational costs [4]. The third, **GAPNet**, integrated Global Average Pooling (GAP) to minimize the parameter count while reducing the risk of overfitting [3]. Each model was trained for **300 epochs** to ensure robust evaluation and generalization.

4.3. Generation 3: Model Integration

In the final phase, the best-performing components from Generation 2 were combined to further enhance performance and to balance speed and accuracy. **KernelNet** reduces the parameter count by using 3x3 kernels in combination with 20% dropout to improve generalization. **DilateNetGAP** integrates dilated convolutions for enhanced spatial feature extraction [4] and GAP to replace the Flatten operation, significantly reducing parameters [3]. The model was trained for **300 epochs** and emerged as the most efficient architecture, achieving the lowest test RMSE and a reduced parameter count compared to earlier generations.

4.4. Training Procedure

The training procedure was standardized across all models to ensure consistency and fair evaluation. The Mean Squared Error (MSE) loss function was used to measure prediction accuracy [7]. The models were trained using the Stochastic Gradient Descent (SGD) optimizer with an initial learning rate of 0.0001 [5]. A learning rate scheduler was applied to adaptively reduce the learning rate when the validation loss plateaued.

Each model was trained for up to **300 epochs** with a batch size of **10**, ensuring sufficient updates while managing computational resources. Early stopping was implemented to halt training if the validation loss did not improve for **20 consecutive epochs**. Training metrics, including loss, RMSE, and validation performance, were monitored and logged at each epoch. Model checkpoints were saved at the epoch corresponding to the lowest validation loss to preserve the best-performing weights [6].

4.5. Evaluation and Challenges

All models were evaluated using test RMSE to quantify prediction accuracy. A paired t-test was conducted post hoc to confirm the statistical significance of improvements between generations. While model design proceeded smoothly, challenges such as convergence instability, computational constraints, and the need for careful hyperparameter tuning were encountered during the training phase. These challenges were mitigated through systematic adjustments to training parameters and resource management strategies. During critical phases, external tools like ChatGPT provided clarity and feedback, assisting in refining methodologies and generating insights for performance improvements [8].

5. RESULTS

5.1. Training and Test Metrics

Throughout the training stage, several key metrics were calculated and analyzed to evaluate the models' convergence and generalization. The loss function used was Mean Squared Error (MSE), computed as:

$$\text{Loss} = \frac{1}{n}\sum_{i=1}^{n}(v_i - \hat{v}_i)^2, \tag{4}$$

where v_i is the true velocity, $\hat{v}_i$ is the predicted velocity, and n is the total number of samples [7]. This equation applies to both training loss (avg_loss) and test loss (avg_test_loss).

The Root Mean Squared Error (RMSE) was used to measure the standard deviation of residuals:

$$\text{rmse} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(v_i - \hat{v}_i)^2}, \tag{5}$$

while the logarithm of RMSE, defined as:

$$\text{log\_rmse} = \log(\text{rmse}), \tag{6}$$

was computed to handle variations in scale. These metrics, including test RMSE (test_rmse) and its logarithmic equivalent (log_test_rmse), were critical in understanding model performance. The results are summarized in Table 1, showcasing how each model performed during training and testing [6, 8].

Model	Parameters (M)	Training Loss	Test Loss	Training RMSE	Test RMSE	Log Test RMSE
Base Model	38.4	0.25834	2.43421	0.50827	1.56020	0.19318
GAPNet	0.535	2.86976	3.77800	1.69404	1.94371	0.28863
DilateNetGAP	**0.502**	**1.92812**	**2.58312**	**1.38857**	**1.60721**	**0.20607**
KernelNet	30.2	0.76844	2.80730	0.87661	1.67550	0.22414
SiLUNet	38.4	0.39258	2.30997	0.62656	1.51986	0.18180
DilateNet	22.4	0.90750	2.46732	0.95263	1.57077	0.19611

Table 1. Training and Test Metrics for CNN Models

5.2. Validation Performance Metrics

To assess the models' generalization capabilities, additional metrics, including inference time, Mean Absolute Error (MAE), and the Coefficient of Determination (R^2), were computed on the validation dataset. The inference time (T_{inf}) measured the processing time for a single validation sample in milliseconds. The Mean Absolute Error (MAE), defined as:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|v_i - \hat{v}_i|, \tag{9}$$

quantified the average magnitude of prediction errors. The R^2 score, which measures how well the predictions explain variance in the true values, was computed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(v_i - \hat{v}_i)^2}{\sum_{i=1}^{n}(v_i - \bar{v})^2}, \tag{10}$$

where $\bar{v}$ is the mean of the true values [5, 8]. The validation metrics are summarized in Table 2, highlighting how DilateNetGAP achieved a favorable trade-off between accuracy and speed.

Model	Inference Time (ms)	RMSE	MAE	R^2
Base Model	0.035116	1.455111	1.075233	0.964852
GAPNet	0.015214	1.682724	1.306023	0.952996
DilateNet	0.030518	1.264666	0.914189	0.973450
DilateNetGAP	**0.010509**	**1.411116**	**0.969049**	**0.966945**
KernelNet	0.008181	1.595109	1.225366	0.957764
SiLUNet	0.039998	1.343386	1.014406	0.970042

Table 2. Validation metrics for CNN models. **DilateNetGAP** achieves a good balance between accuracy and inference speed.

5.3. Visual Analysis

Further insights into the models' performance are provided through visual analysis. Figure 2 presents a scatter plot of RMSE versus inference time, demonstrating how DilateNetGAP achieves an optimal trade-off between speed and accuracy. Additionally, Figure 4 highlights the prediction error distributions, where models like DilateNetGAP exhibit narrower distributions, indicating greater consistency and reduced variability.

6. DISCUSSION

The performance results, summarized in Table 1 and Table 2, highlight the trade-offs between accuracy, inference speed, and model consistency across different architectures.

6.1. Model Performance Analysis

DilateNetGAP achieved the fastest inference time ($T_{\text{inf}} = 0.010509\,\text{ms}$) while maintaining competitive RMSE (1.411116), making it ideal for real-time tasks requiring both speed and reliability. SiLUNet demonstrated the lowest RMSE (1.343386) and exhibited superior predictive accuracy; however, its higher inference time (0.039998 ms) limits its practicality in latency-sensitive applications. DilateNet offered

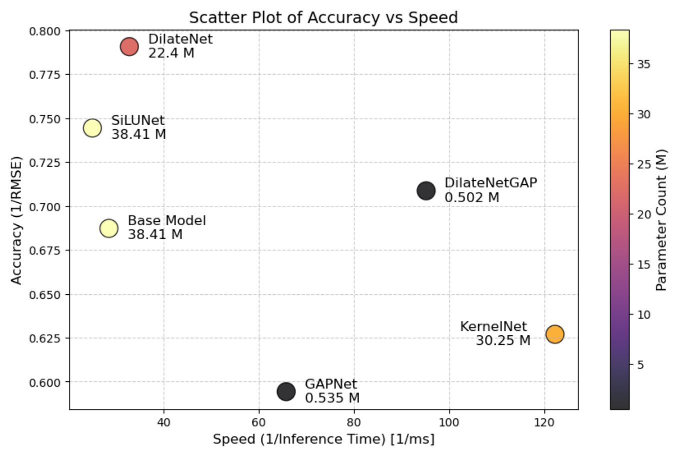

Fig. 2. Scatter plot of RMSE vs. Inverse Inference Time. **DilateNetGAP** demonstrates an optimal balance between accuracy and speed.

balanced performance with an RMSE of 1.264666 and moderate inference time (0.030518 ms), making it suitable for computationally constrained scenarios [4, 3, 8].

6.2. Visual Analysis

To further evaluate model consistency and prediction accuracy, two visualizations were analyzed. Figure 3 shows the scatter plot of true versus predicted values across all models. DilateNet and DilateNetGAP exhibit tighter clustering along the diagonal line, indicating strong alignment with ground truth values and better generalization. In contrast, GAPNet and KernelNet displayed greater scatter, suggesting difficulty in capturing complex spectrogram patterns [7, 6].

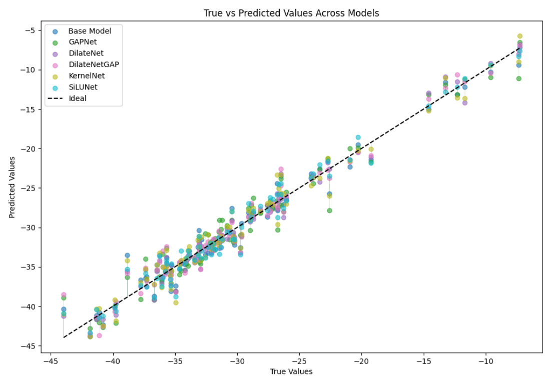

Fig. 3. Scatter plot of true vs. predicted values across models.

The error distributions shown in Figure 4 highlight the consistency of model predictions. DilateNetGAP and SiLUNet demonstrated narrower error distributions, reflecting reduced variability and more reliable predictions. GAPNet and KernelNet, however, displayed broader error spreads, indicating less stable performance and limited capacity to model complex data [3].

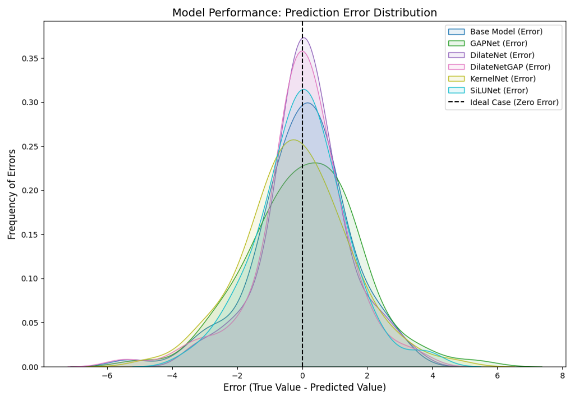

Fig. 4. Prediction error distributions across models.

6.3. Trade-offs and Observations

The results highlight trade-offs between accuracy, speed, and complexity. DilateNetGAP balanced reliability and speed, making it ideal for real-time use. SiLUNet achieved higher accuracy but was slower, while GAPNet prioritized speed at the cost of accuracy. KernelNet's high parameter count offered no significant performance gains, emphasizing the need for efficient design [5, 4].

6.4. Future Improvements

Future enhancements include incorporating attention mechanisms to improve feature extraction and employing pruning or quantization to reduce inference time while maintaining accuracy. Robust data augmentation, such as synthetic noise, can enhance generalization on noisy data. Additionally, uncertainty estimation methods like Bayesian Neural Networks or Evidential Learning can increase prediction reliability in safety-critical applications [6, 8].

6.5. Summary

The analysis identifies DilateNetGAP as the most balanced model, combining speed and accuracy for real-world use. SiLUNet offered the highest accuracy but was slower, while DilateNet balanced performance for resource-constrained scenarios. These findings emphasize the importance of tailored solutions to balance accuracy, efficiency, and consistency across diverse applications [3, 8].

7. REFERENCES

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