TDS2101 Data science fundamentals

Multimedia University (MMU)

# Brain Tumour Detection with Machine Learning

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# Overview

MAJOR SECTIONS OF THIS PROJECT PRESENTATION


- Introduction
- Project Objectives
- Dataset Description
- Research Methodology & Model
- Initialization, Training, and Tuning of Hyperparameters
- Performance evaluation, comparison, and discussion of the results
- Conclusion &Future Enhancements

# Introduction

- A brain tumour is an abnormal growth of cells in the brain. It can be malignant (cancerous) or benign (noncancerous).
- Magnetic resonance imaging (MRI) is a medical imaging technique, but it is subject to human error and can lead to tragic outcomes.
- Deep learning algorithms may help clinical experts detect the initial stages of the tumour.
- For this research project, a dataset from the Kaggle website will be used, which includes three types of tumours: glioma, meningioma, and pituitary tumours, as well as an MRI of no tumour.

# Project Objectives

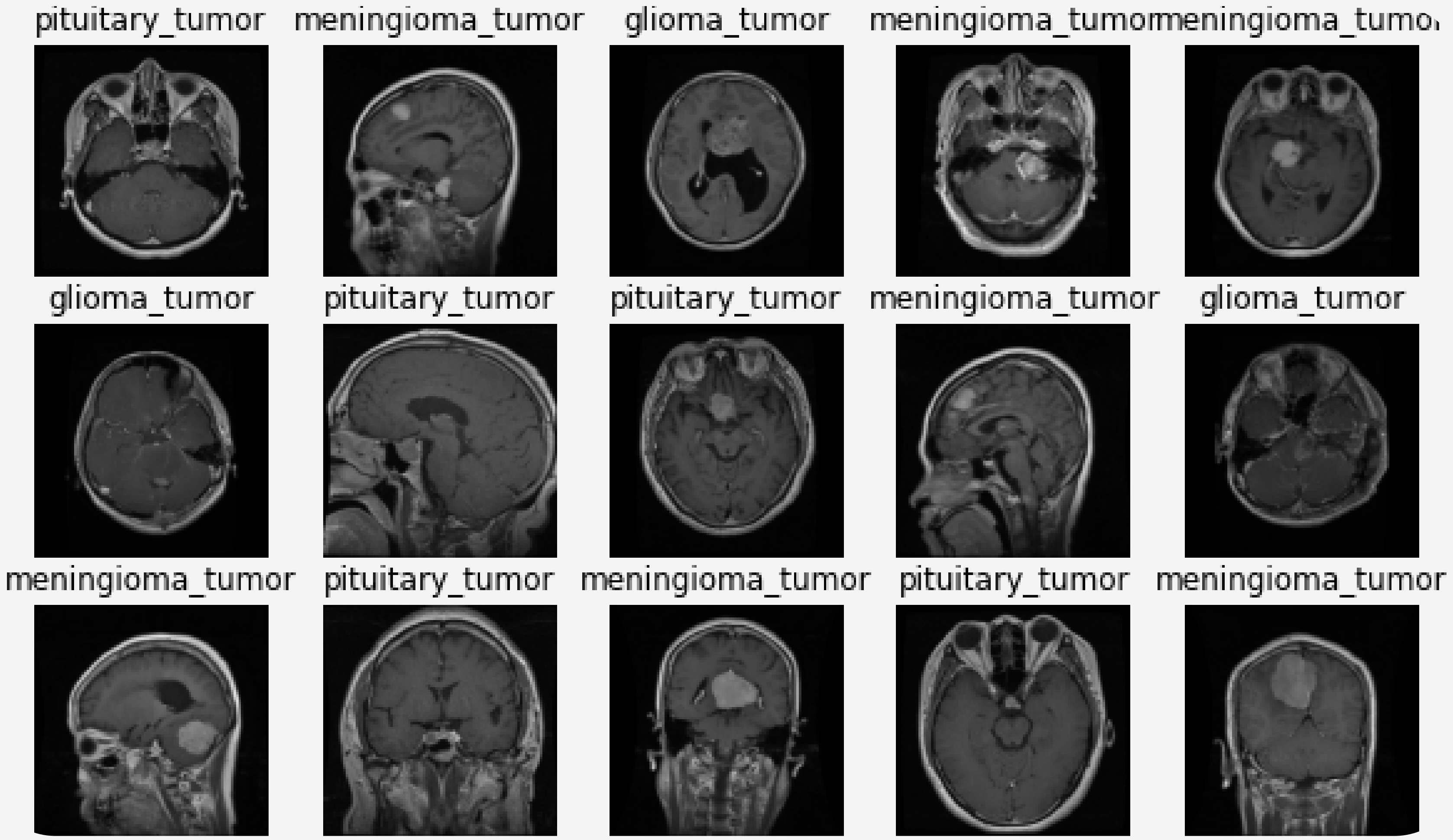
## 01

To compare and find the higher accuracy rates between the deep learning algorithms.

## 02

To compare and find the lower loss rates between the deep learning algorithms.

# Dataset Description




The MRI dataset was acquired from the Kaggle website which will be used for this research project. The dataset contains two directories which are:

**Testing and Training Directories**

# Research Methodology & Model

- In this section, I will show the accuracy and the loss rates using the Adam optimizer, 50 epochs, image size of 224 by 224, and 128 as the batch number.

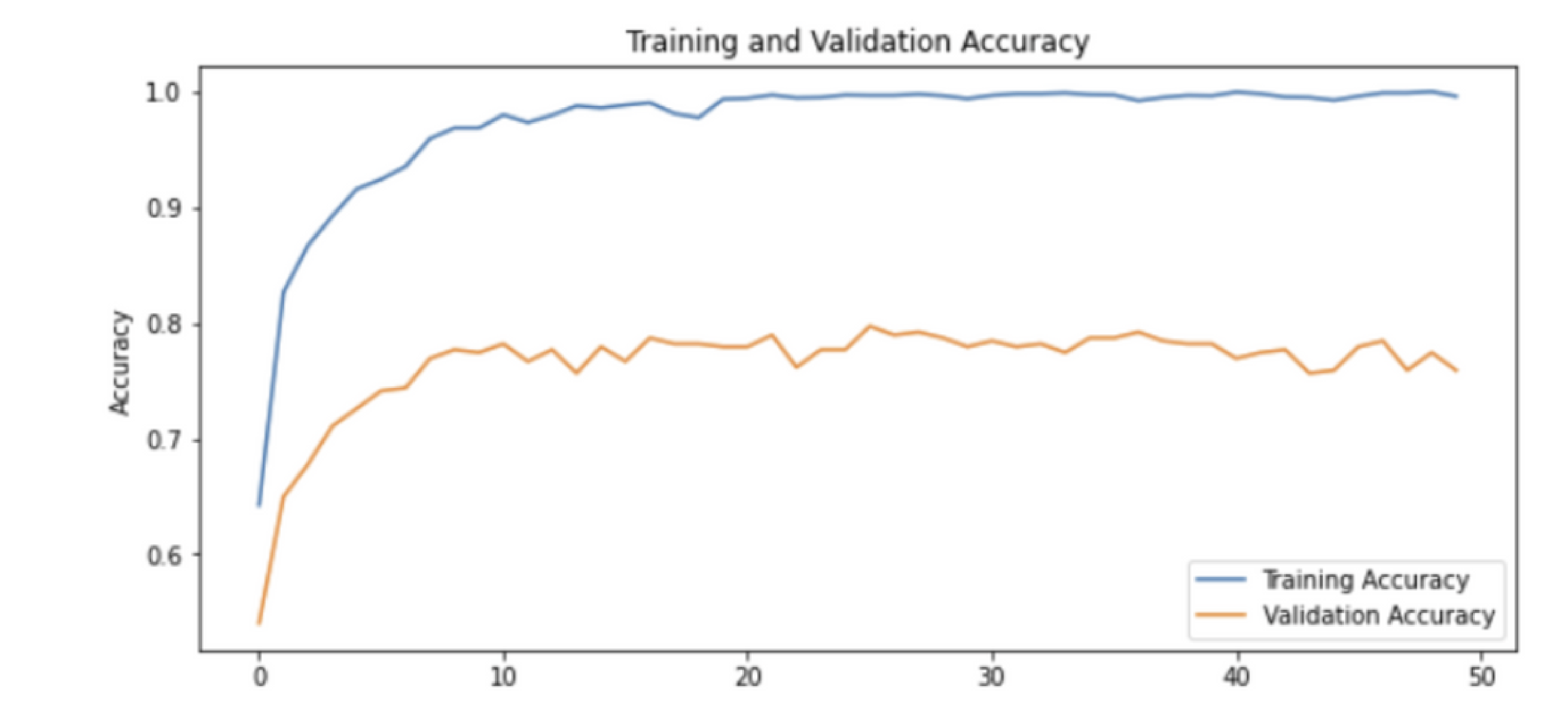
# Research Methodology & Model



**Conventional neural networks (CNN)**

Conventional neural networks (CNN) is a supervised type of Deep learning, mainly used for image and speech recognition.

# Research Methodology & Model



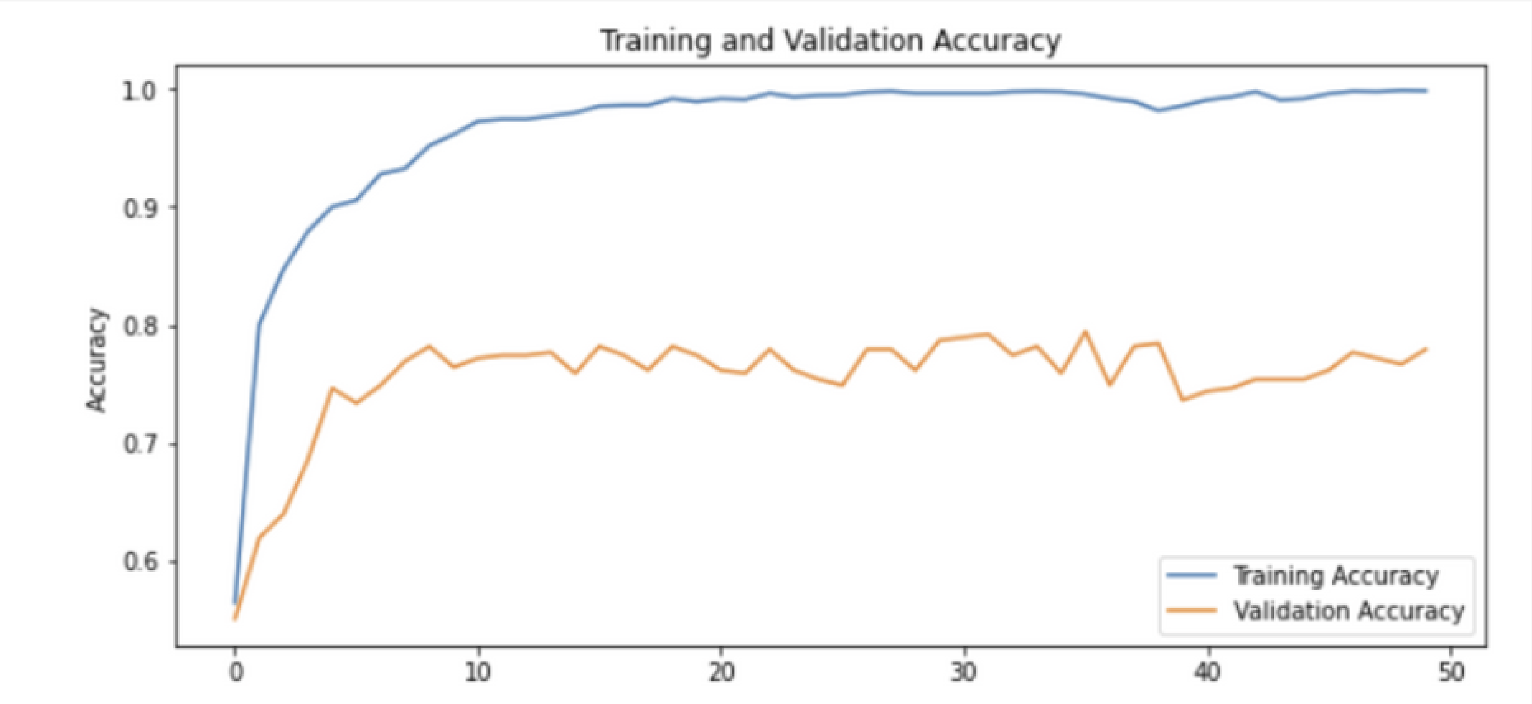


**Transfer Learning (TL) Part 1**

## MobileNetV2

MobileNetV2 is a convolutional neural network architecture for image classification that was developed by Google.

# Research Methodology & Model



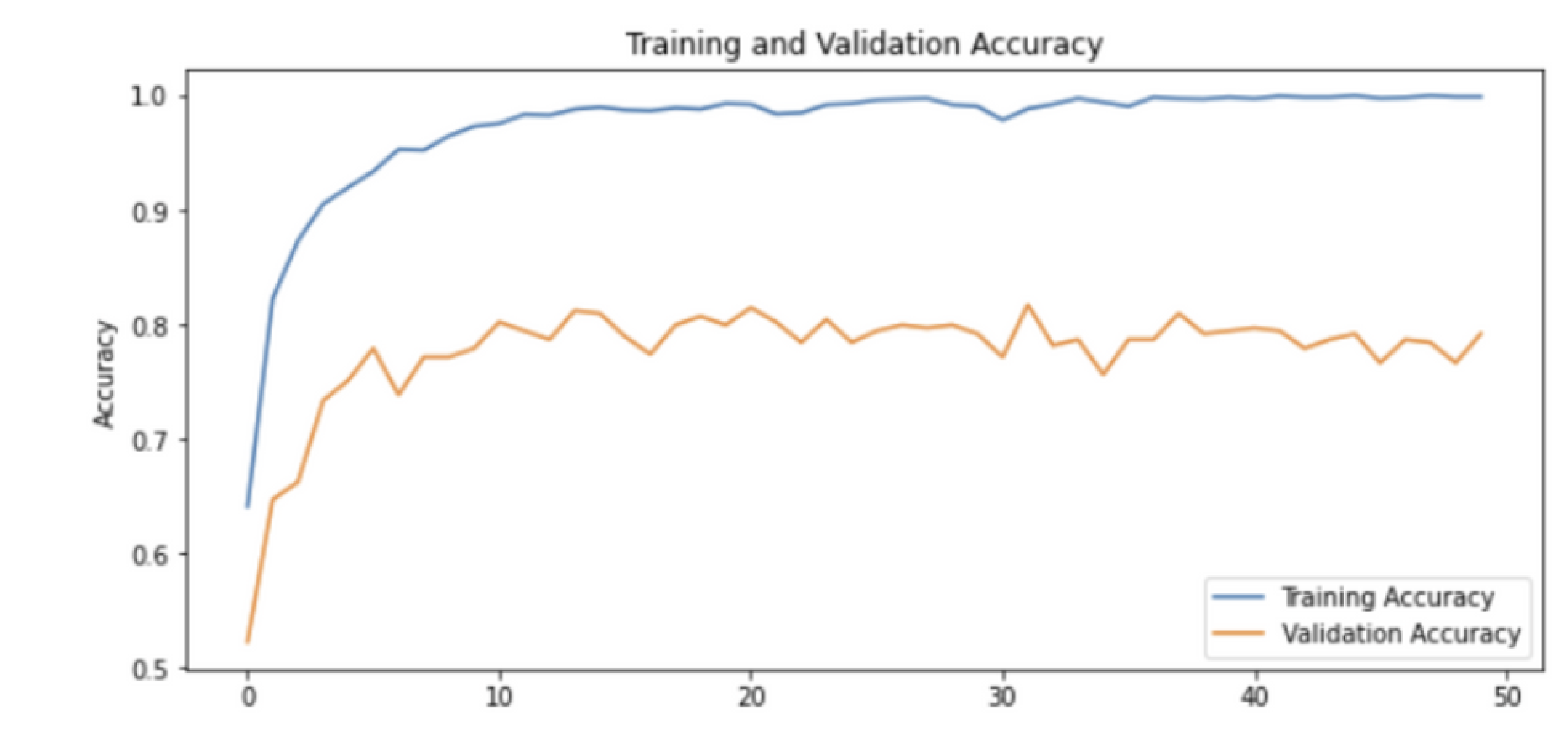


**Transfer Learning (TL) Part 2**

## VGG19

VGG19 is a convolutional neural network model trained on the ImageNet dataset. This model and its variants are used for image classification and other vision tasks.

# Research Methodology & Model





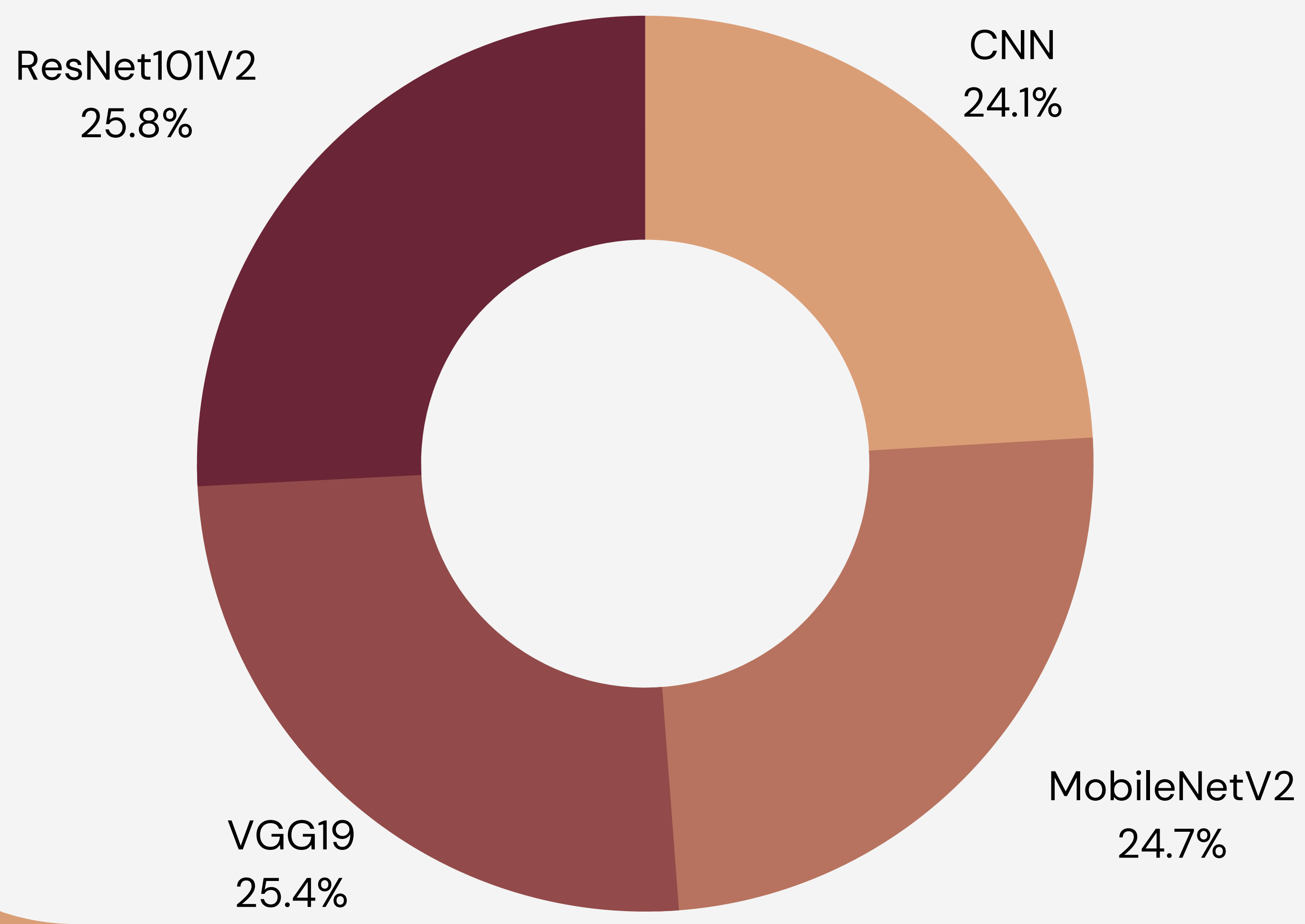
### Transfer Learning (TL) Part 3

## ResNet101V2

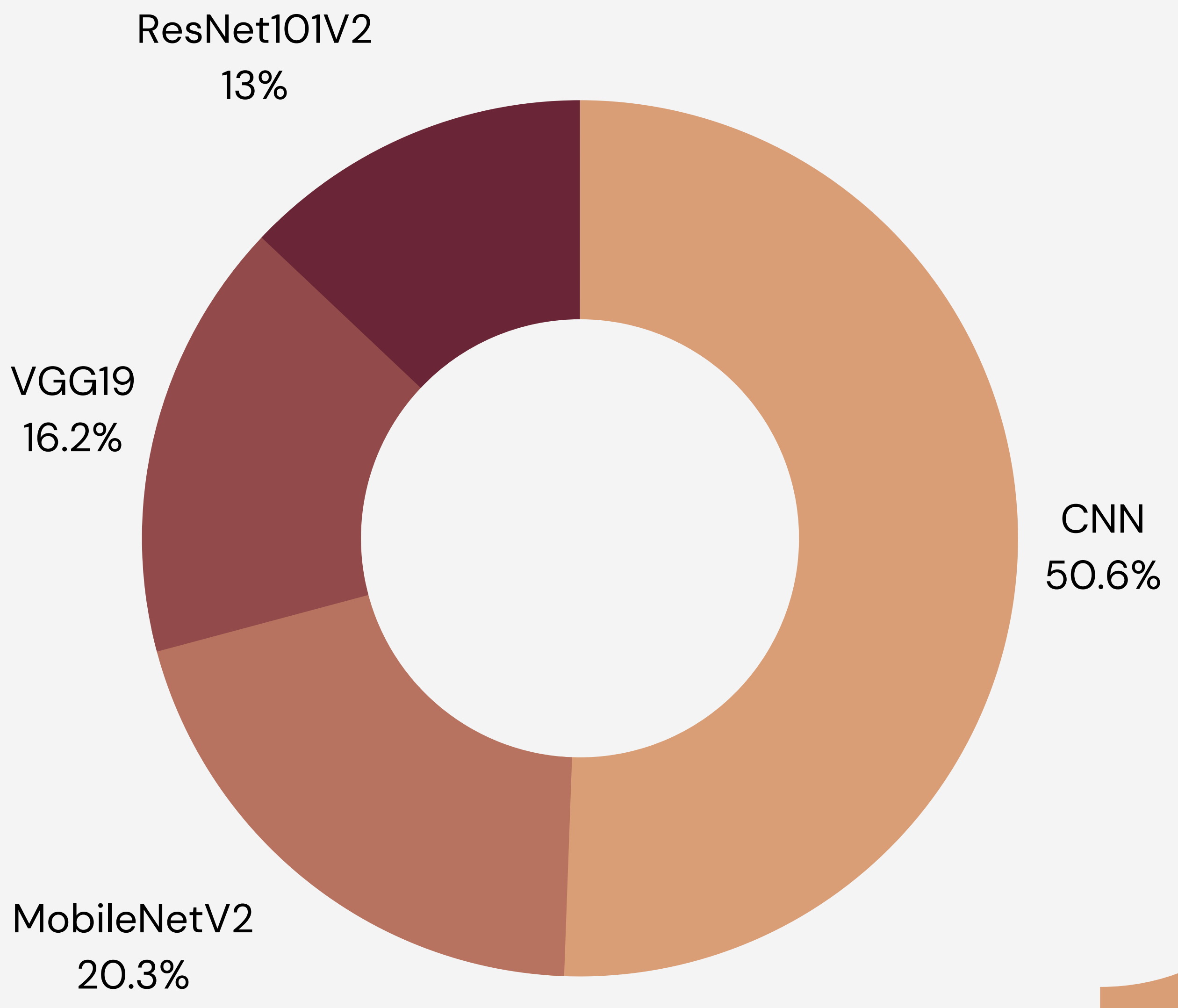
ResNet101V2 is an image recognition convolutional neural network trained to distinguish objects in images.

# Comparison Between Models

## Accurcay Rates Pie Chart



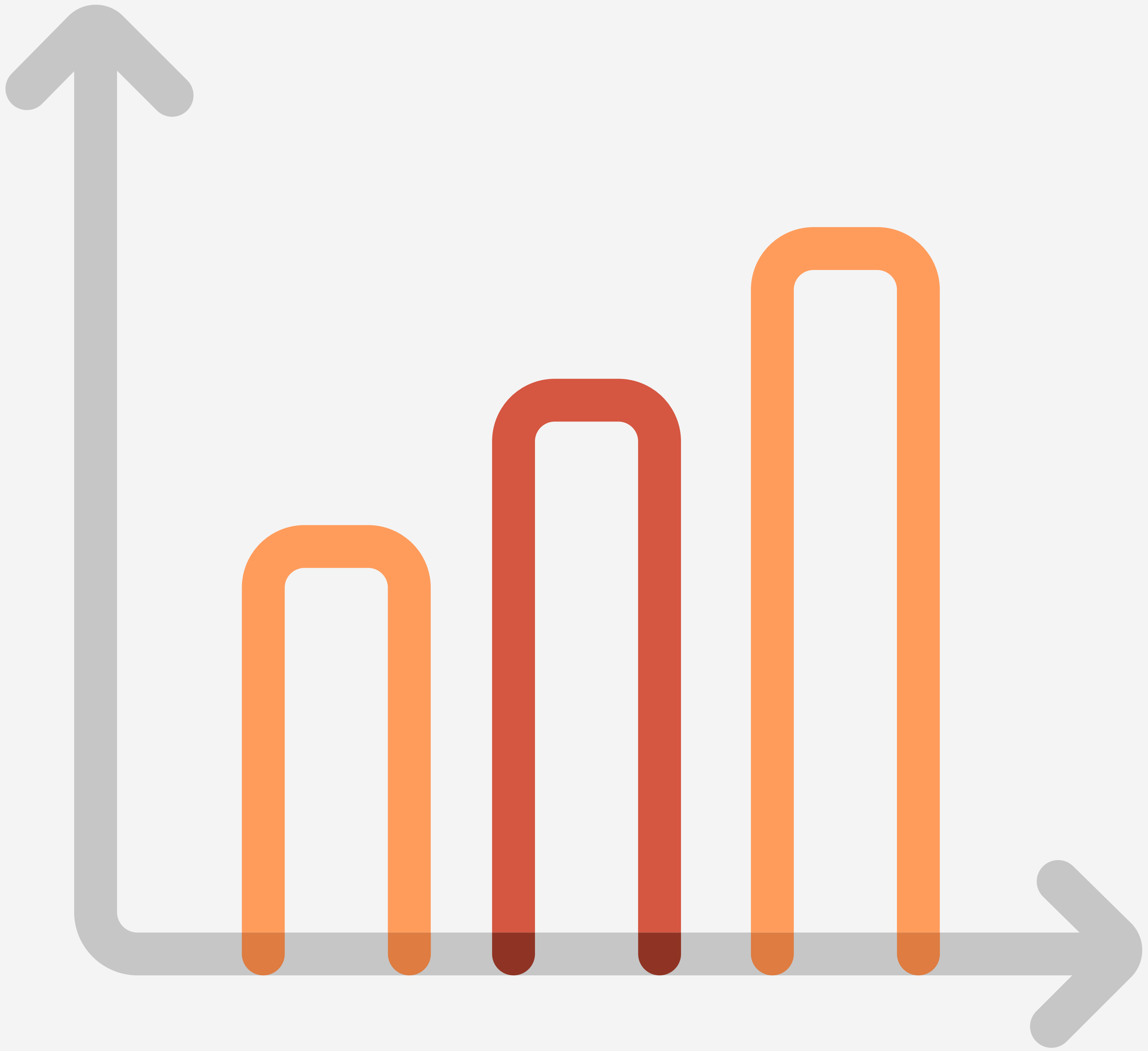

## Loss Rates Pie Chart



# Initialization, Training, and Tuning of Hyperparameters

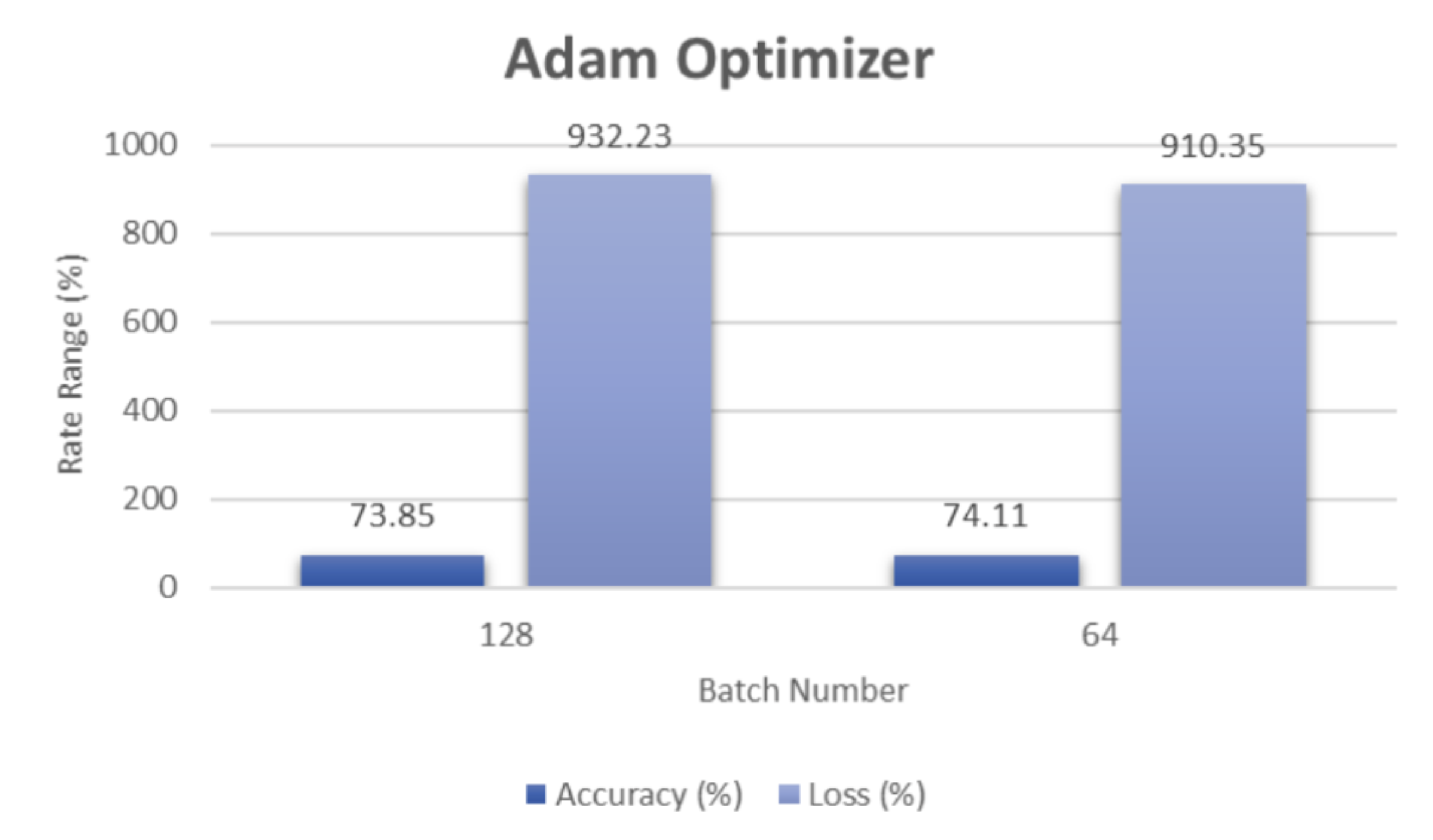
The initialization and tuning of several hyperparameters related to transfer learning and convolutional neural networks.

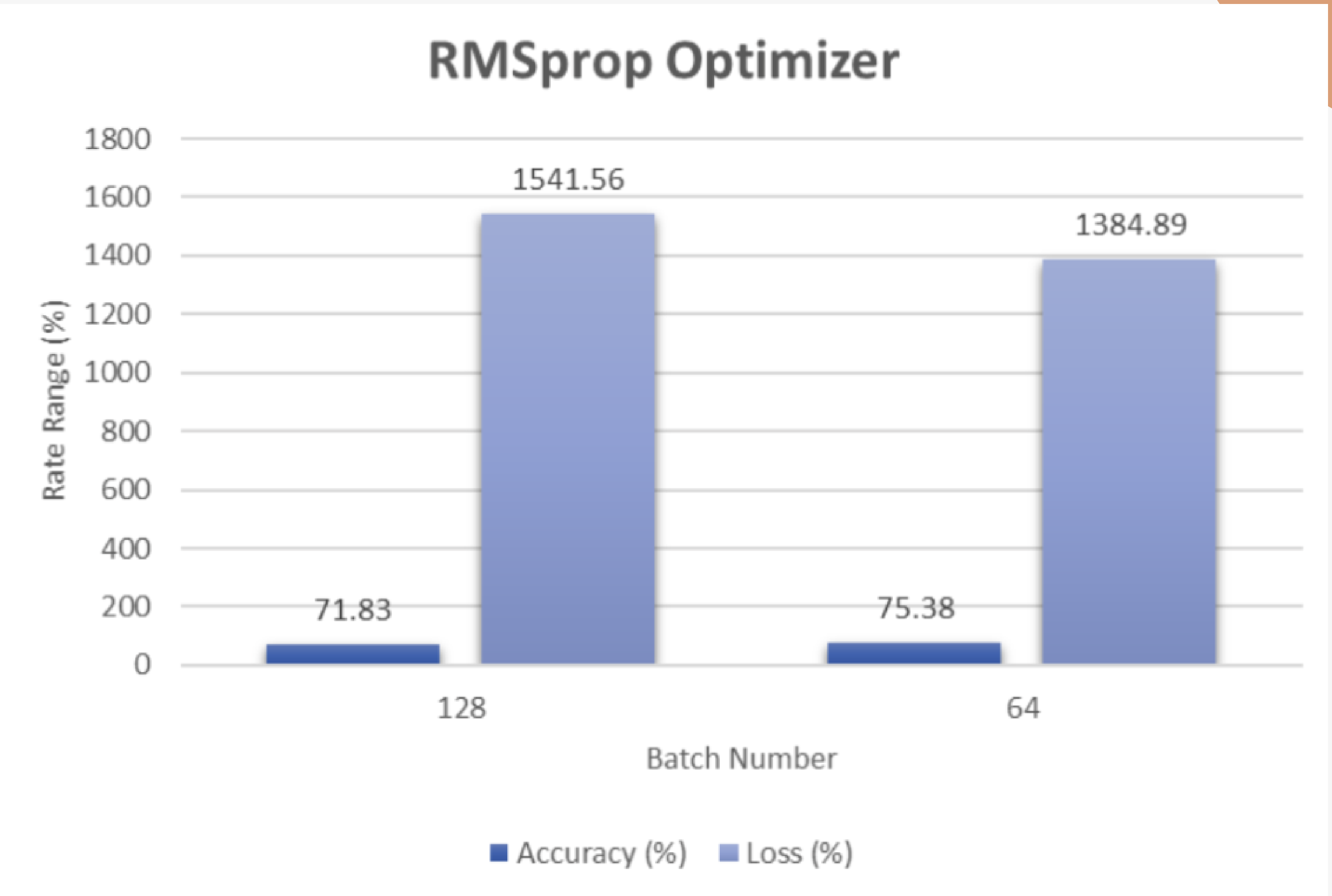
Training the models using different numbers of batches, two optimizers, the image size set to (224,224) and the number of epochs set to 50.



# Results

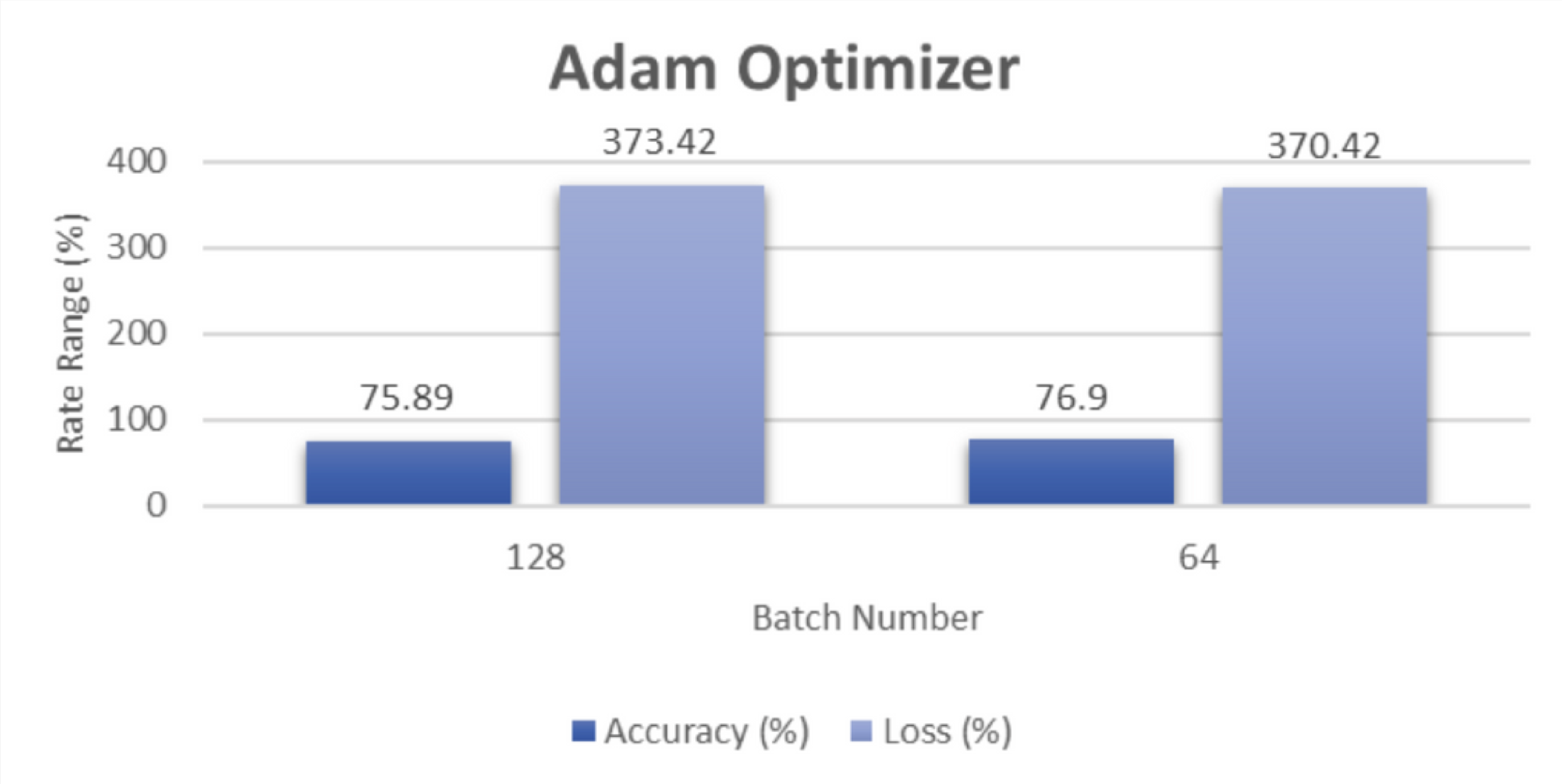
## Conventional Neural Networks (CNN)

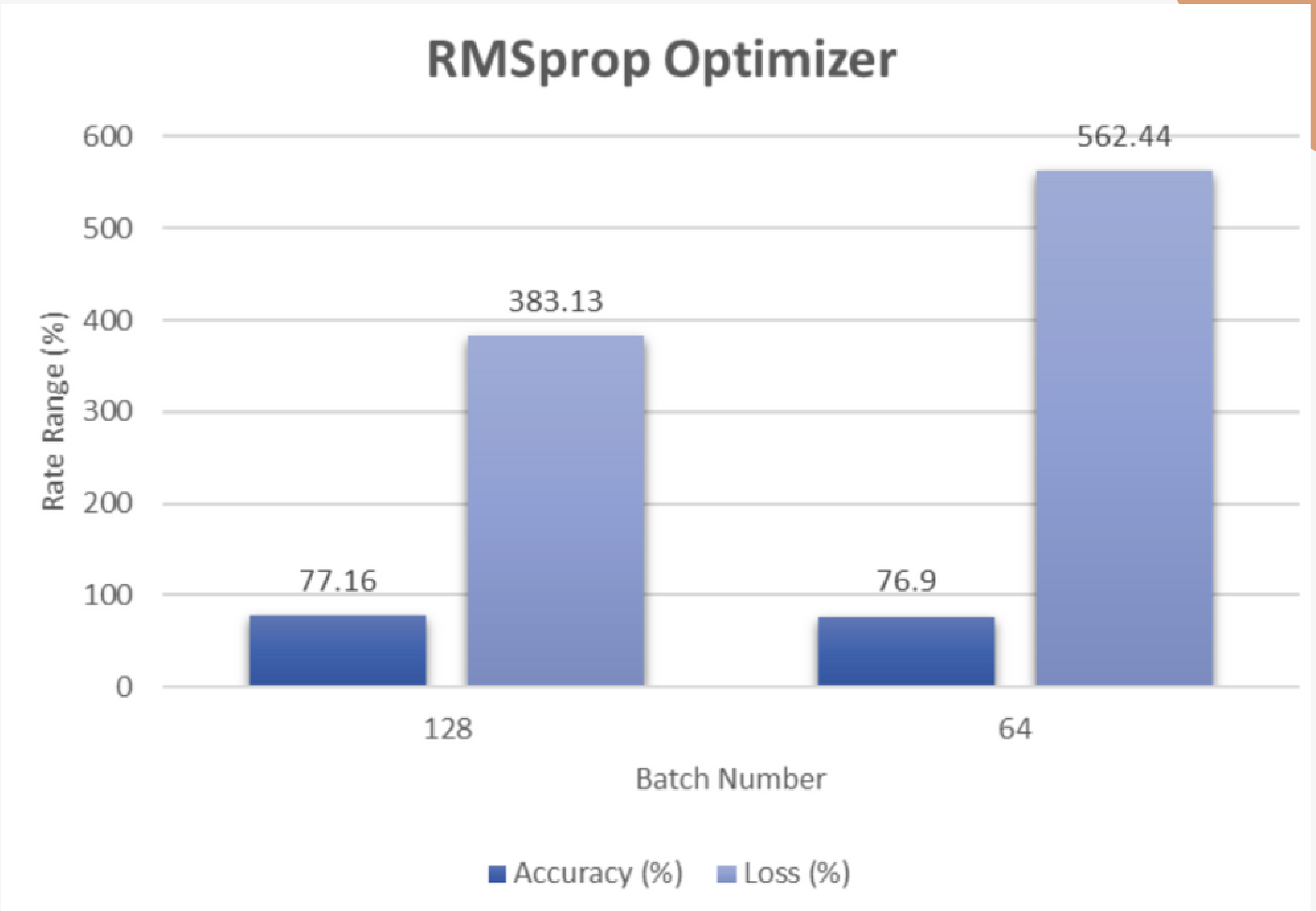


# Results

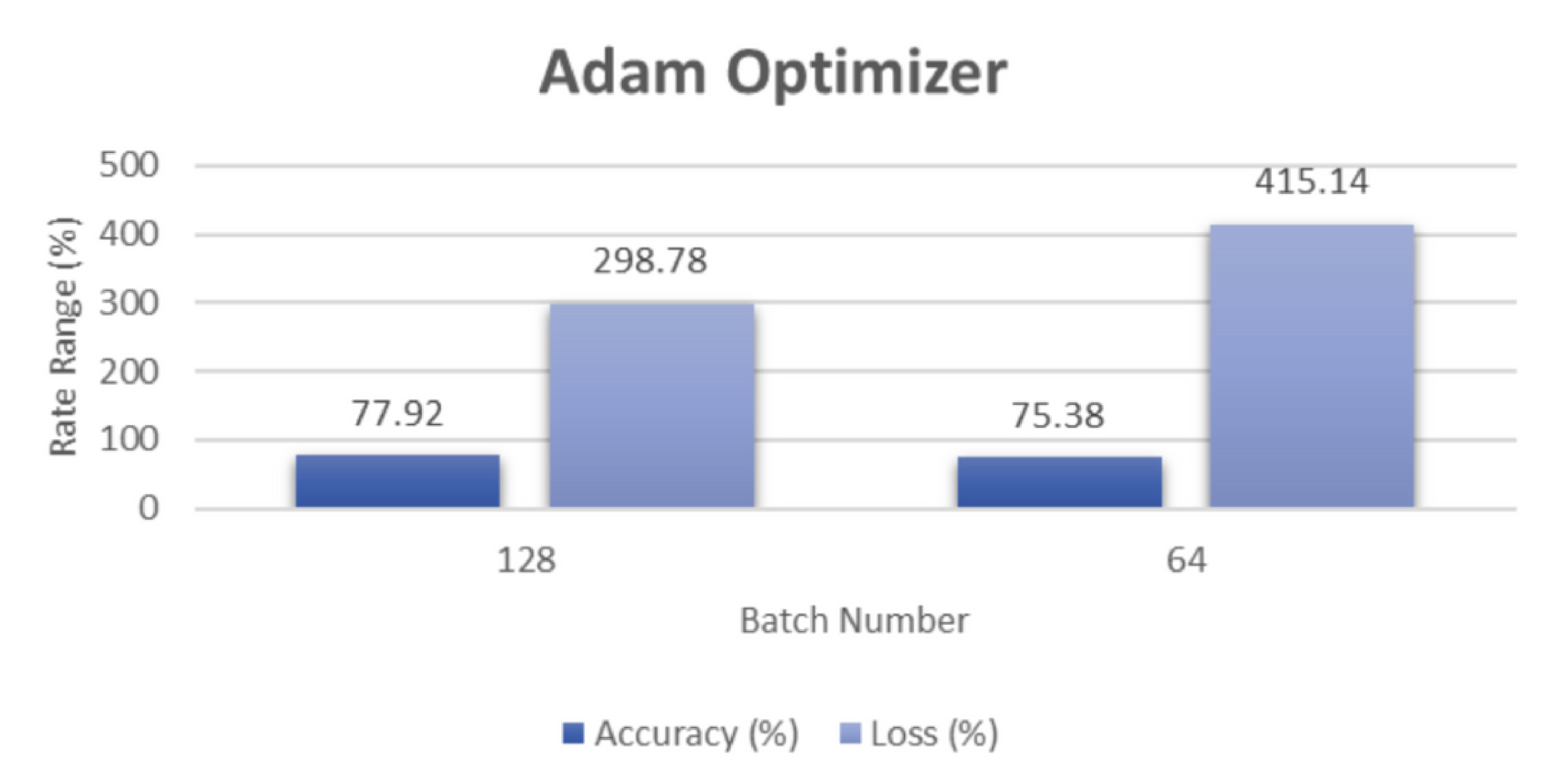
## Transfer Learning (MobileNetV2)

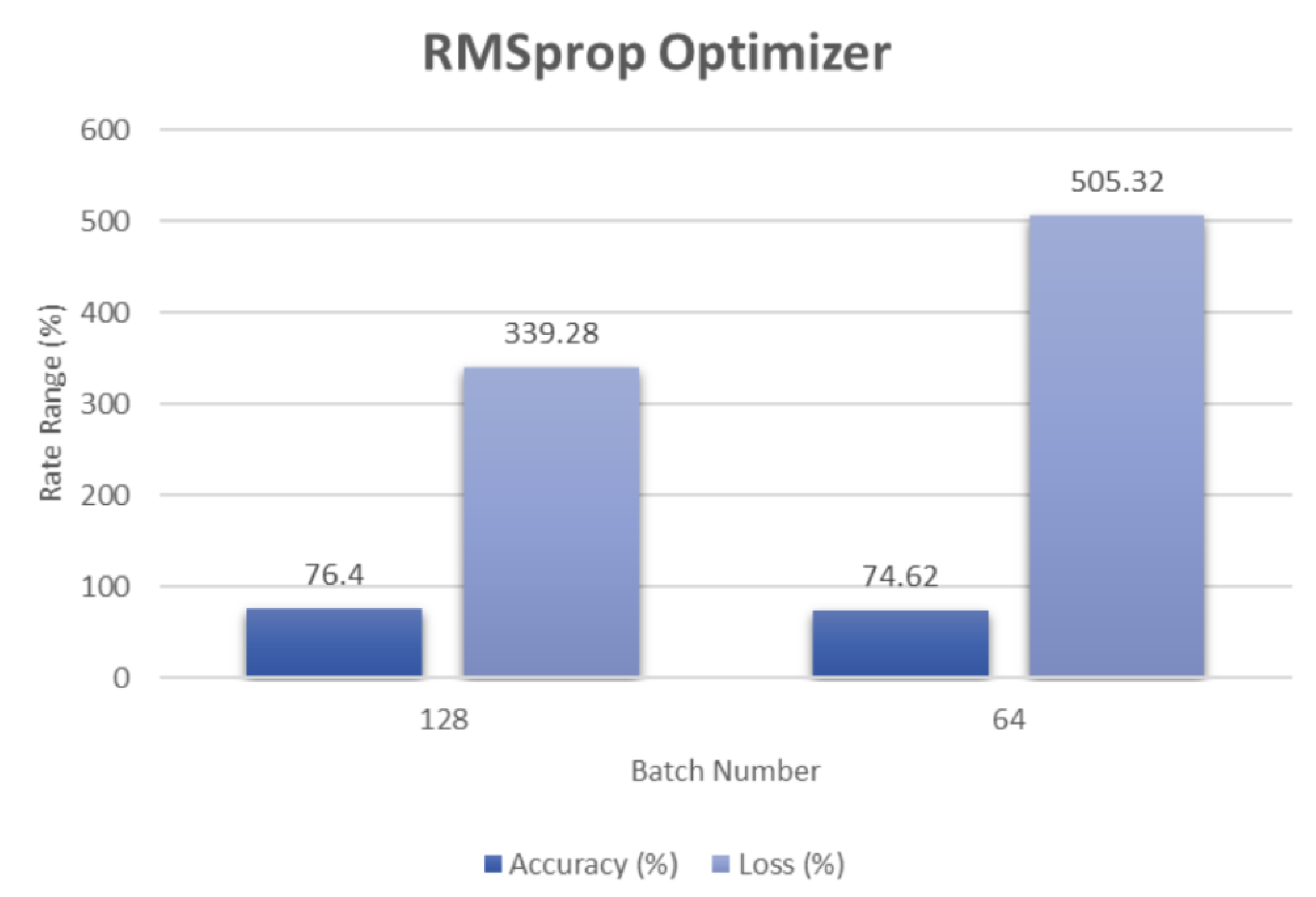


# Results

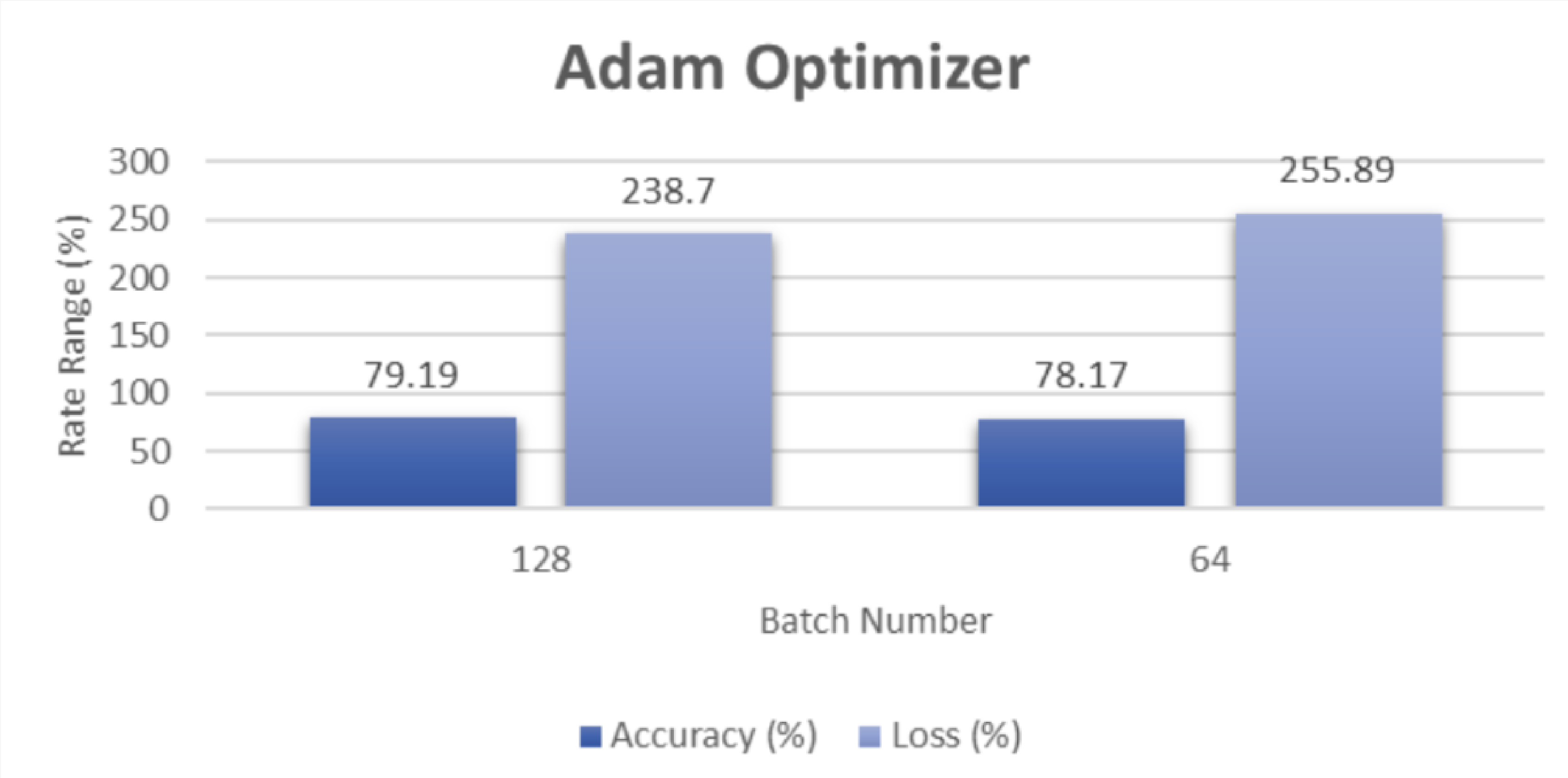
## Transfer Learning (VGG19)

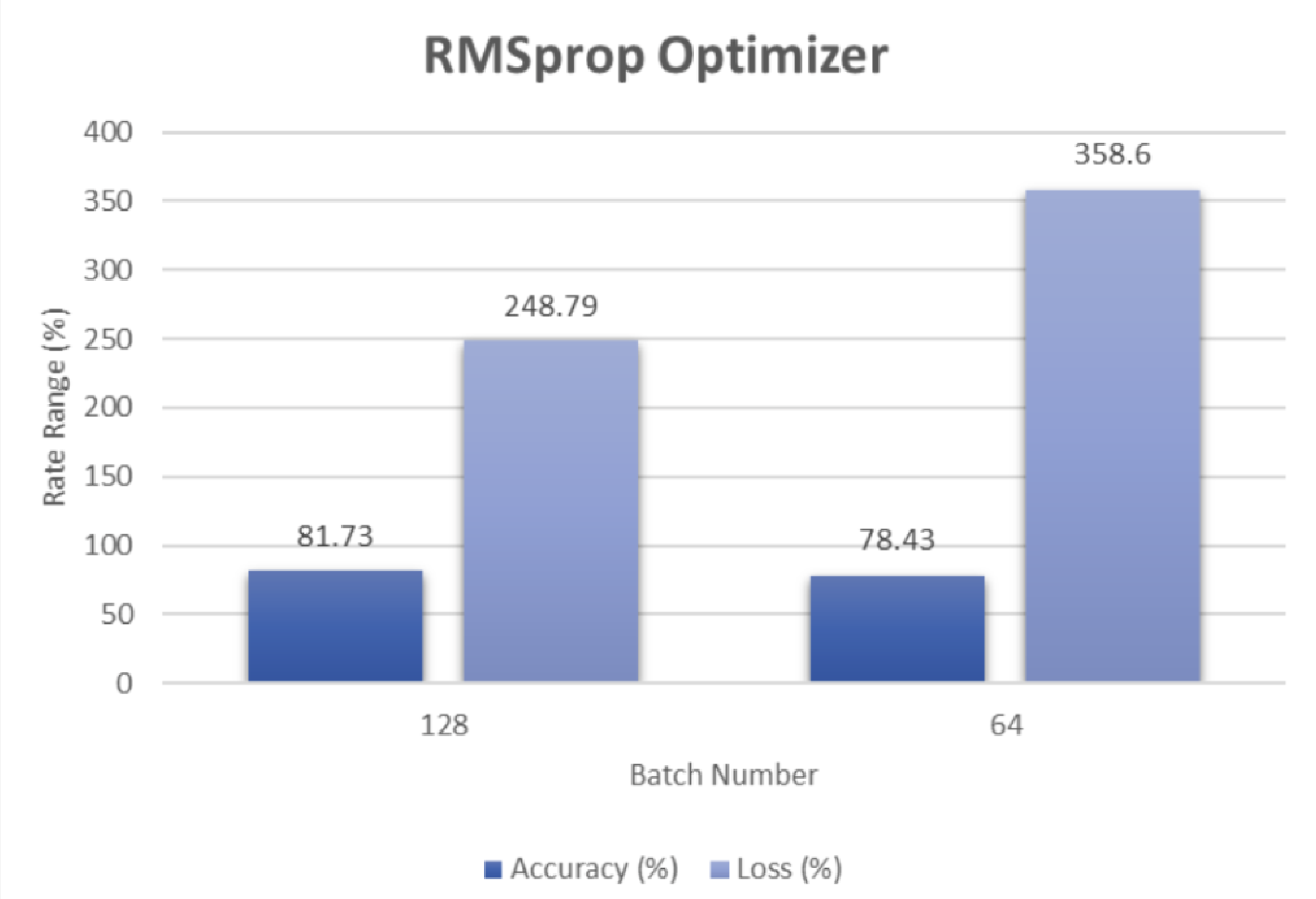


# Results

## Transfer Learning (ResNet101V2)

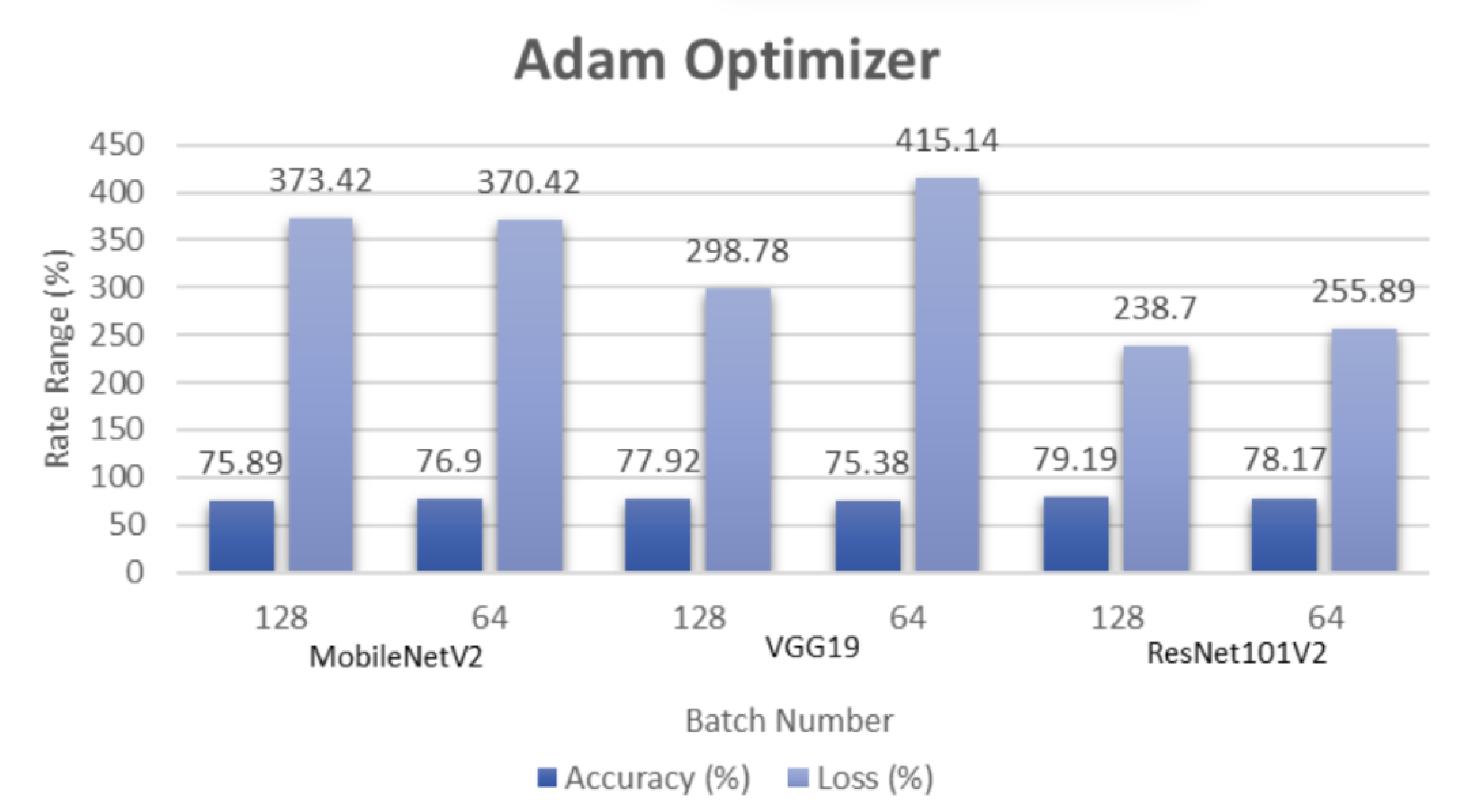


# Performance evaluation, comparison, and discussion of the results

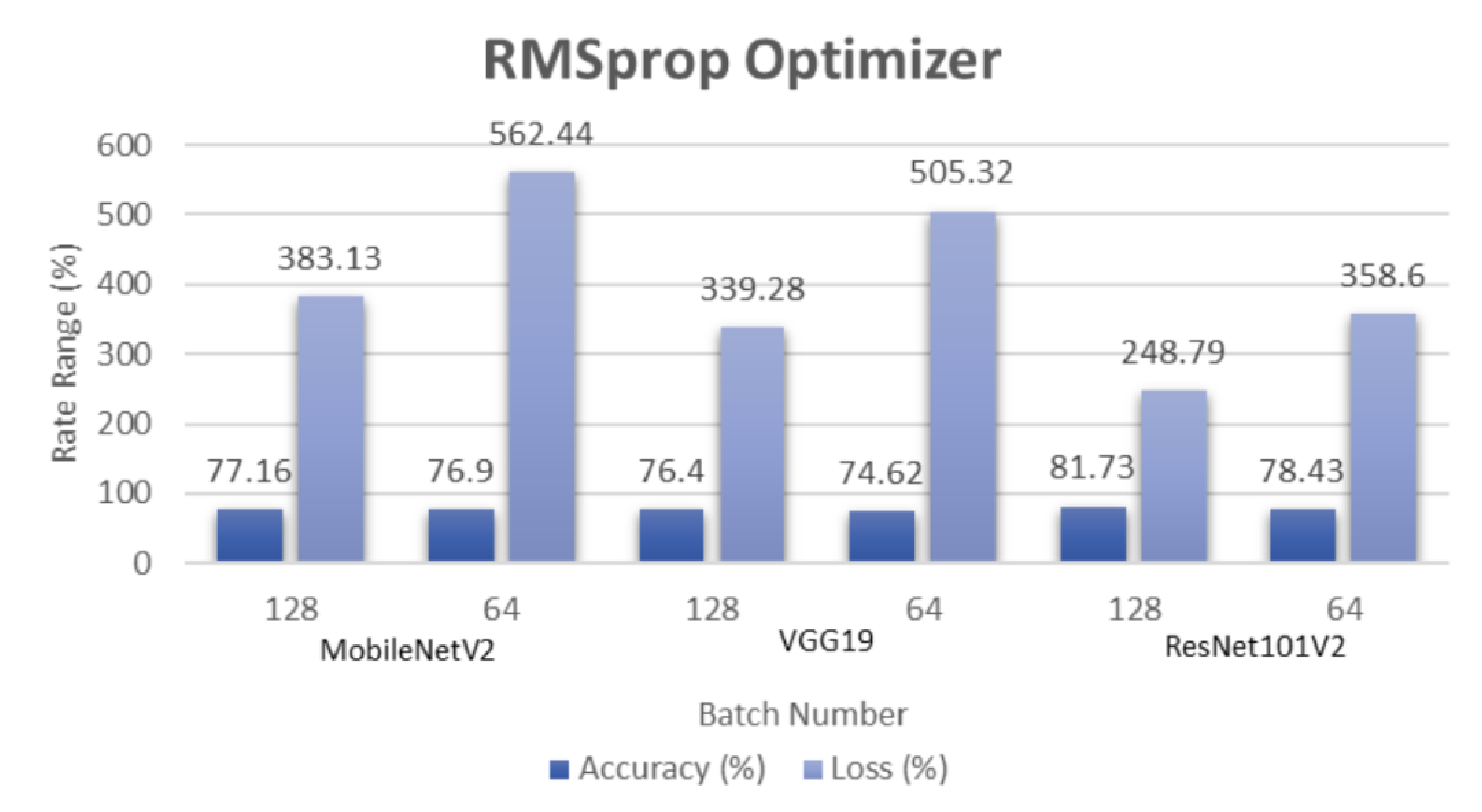
# Comparison of the Machine Learning Models

The ResNet101V2 architecture model has the highest rate of accuracy 79.19%, and the lowest loss rate 238.7%. When the batch number was halved, the ResNet101V2 had the highest accuracy rate at 78.17% and the lowest loss rate at 255.89%.



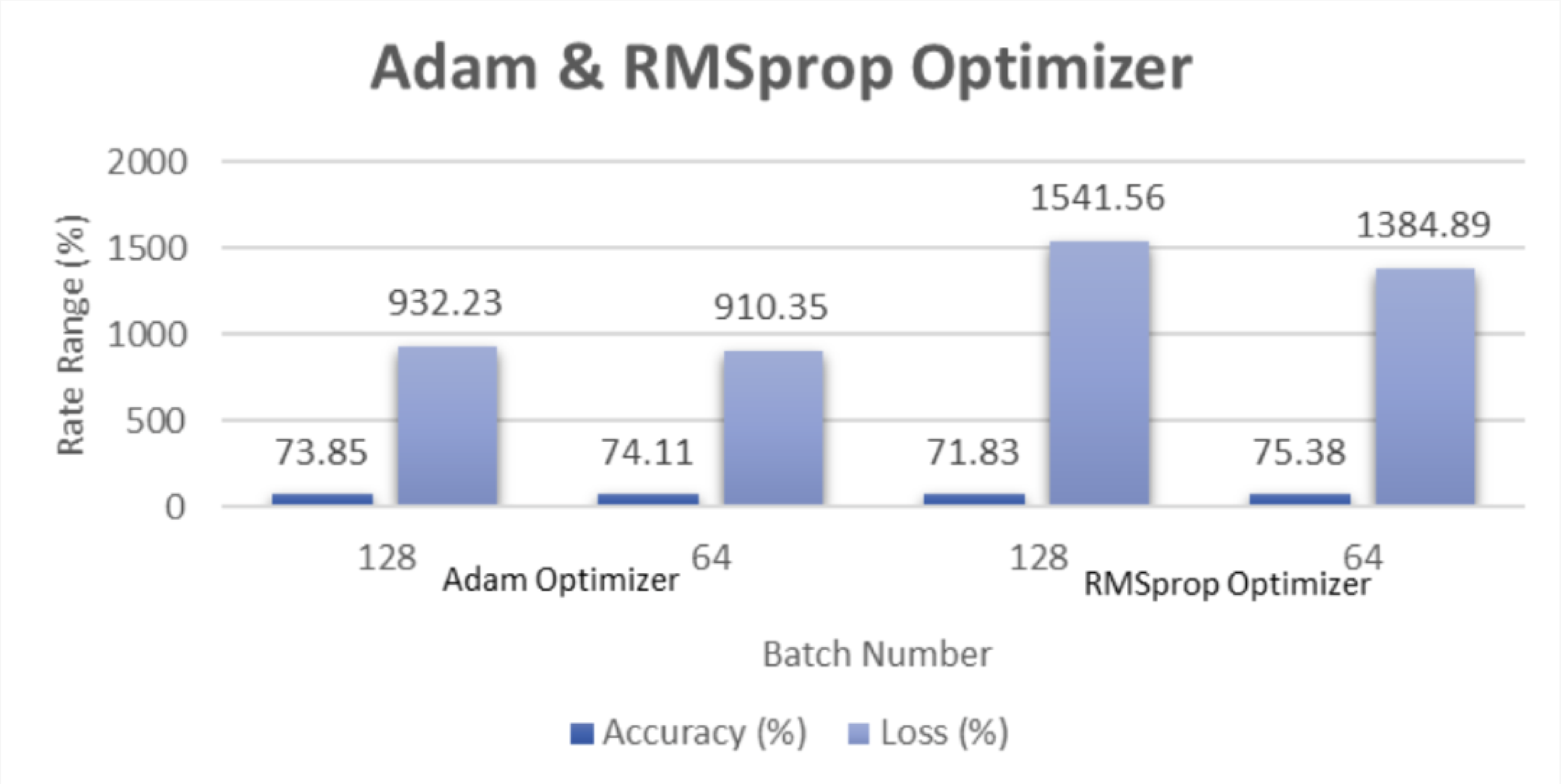
# Comparison of the Machine Learning Models

The optimizer RMSprop with a number of 128 batches, the ResNet101V2 had the highest accuracy rate of 81.73% and the lowest loss rate of 248.79%. When the batch number was decreased to 64, the ResNet101V2 had the highest accuracy rate 78.43%, and the lowest loss rate 358.6%.

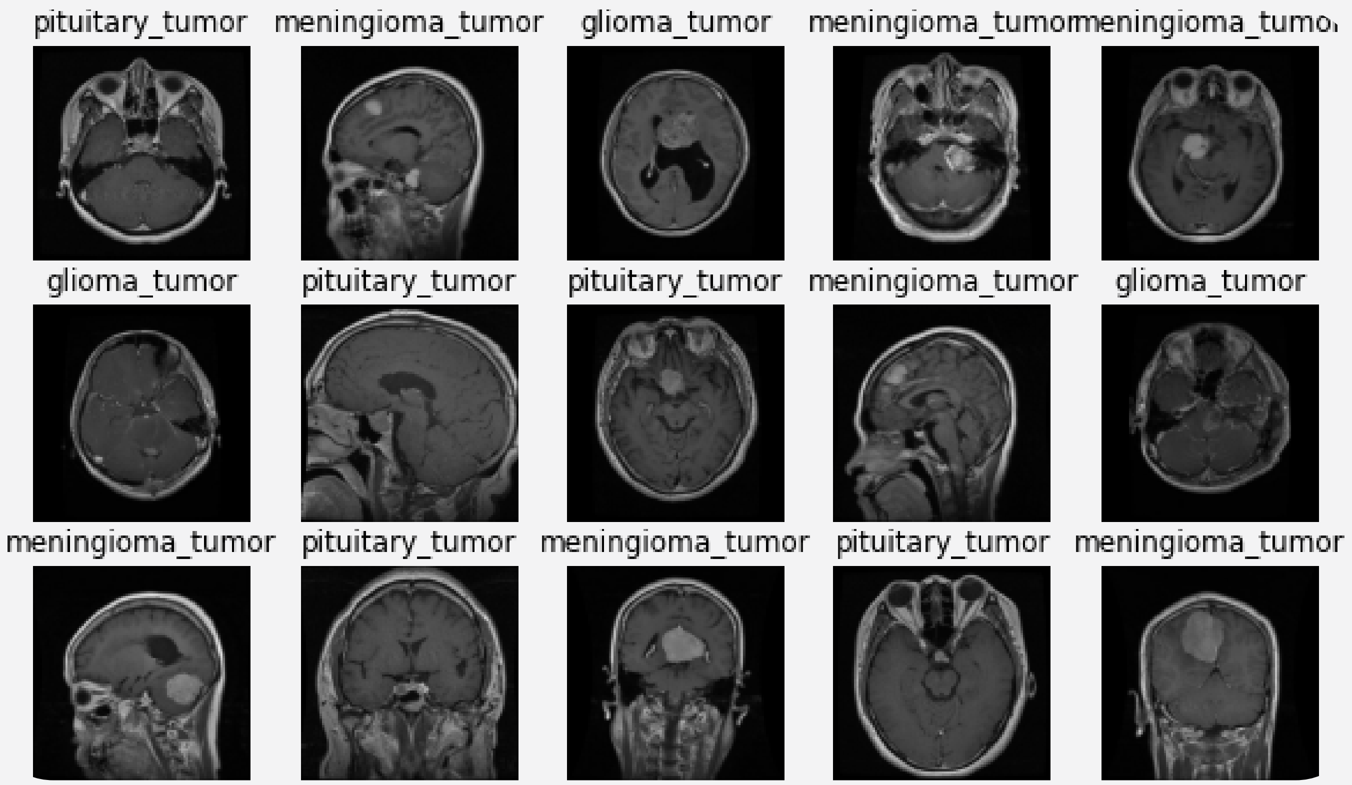


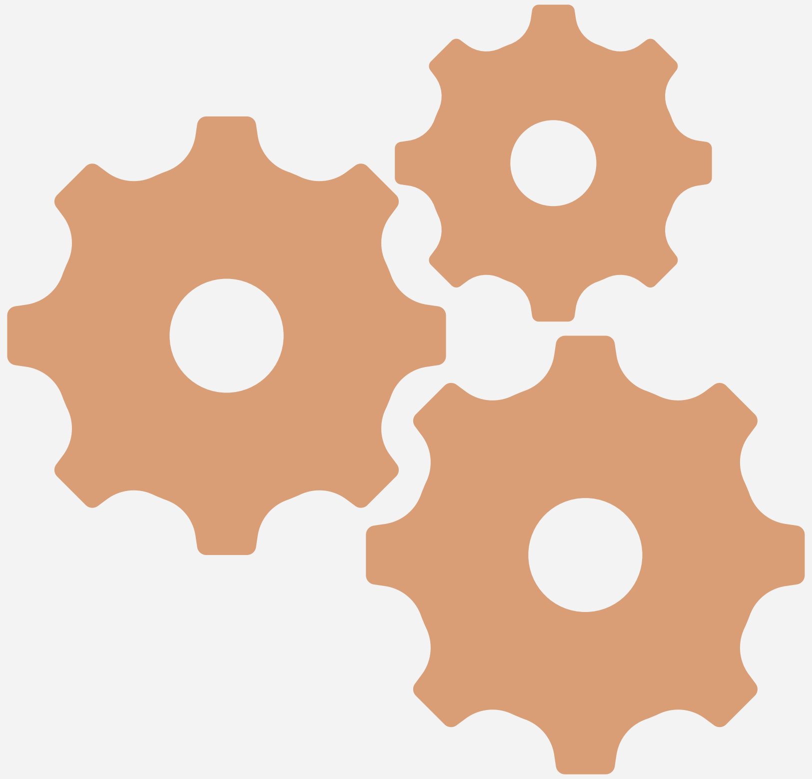
# Comparison of the CNN

Using the CNN model with the number of 128 batches, the Adam optimizer had a higher accuracy rate of 73.85% and a lower loss rate of 932.23%. When the number of batches was halved, the RMSprop optimizer had a higher accuracy rate of 75.38% and the Adam optimizer had a lower loss rate of 910.35%.



# Conclusion



### Lack of data

To address this, more data can be collected or data augmentation can be used.

### Overfitting

To decrease the validation loss caused by overfitting, techniques like regularization, dropout, and early stopping can be used.

# Future Enhancements

Try different datasets or other pre-trained models for transfer learning

Try ensembling, multiple models, to improve the overall performance and also try fine-tuning the pre-trained models.

# thank you for listening