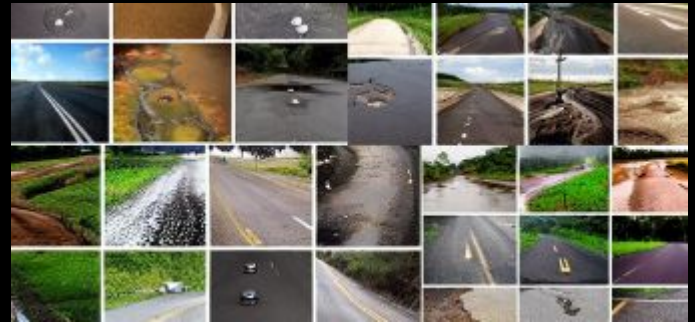


# Unveiling Insights: A Journey into Pothole Detection

Exploring Machine Learning for Safer Roads



Presented by: Anthony Brocco November 10, 2023

## Potholes Impact Road Safety

- The uneven road surfaces created by potholes can lead to vehicle damage and accidents, causing financial burdens.
- Pedestrians face tripping hazards, particularly in poorly lit areas or adverse weather conditions.

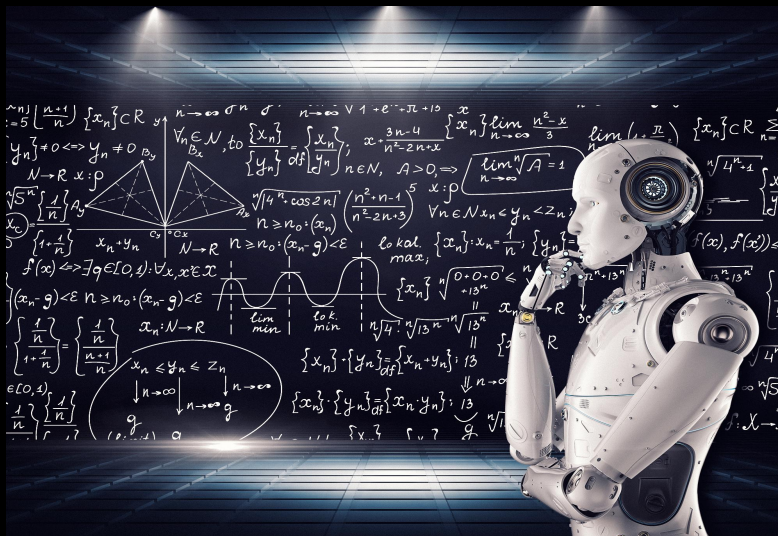
## Potholes Impact Finances

- Fixing roads is being heavily funded by the government and creates a great opportunity for business.



# Why machine learning?

By using machine learning, we can automatically find and fix potholes faster, helping to keep roads safe and reduce risks.





# OUR DATA

Found at

<https://www.kaggle.com/datasets/srajanchoorasia/pothole-dataset>

- Data Characteristics:

- The dataset comprises a total of 30,000 images.
- The "Number of Potholes" column indicates the count of potholes in each image.

- Types of Roads Covered:

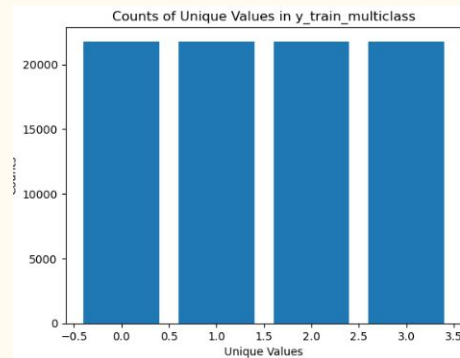
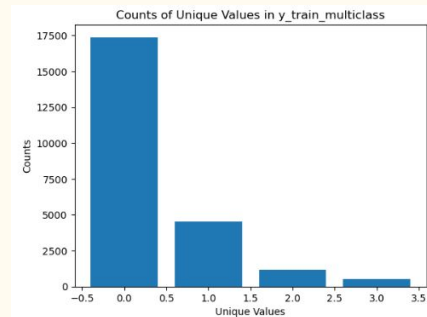
- The images represent diverse road types, including urban streets, highways, and suburban roads.
-

# Balancing our dataset

## Using Image Data Generator

Due to imbalances in our dataset, specifically in the 'Number of Potholes' category, it was necessary to oversample some photos using the following metrics

```
rotation_range=30,  
width_shift_range=0.2,  
height_shift_range=0.2,  
shear_range=0.2,  
zoom_range=0.2,  
horizontal_flip=True,  
fill_mode='nearest'
```



# Goals

- We aimed to first work based on presence of potholes. A binary classification problem
- We then moved to the next step of classifying number of potholes

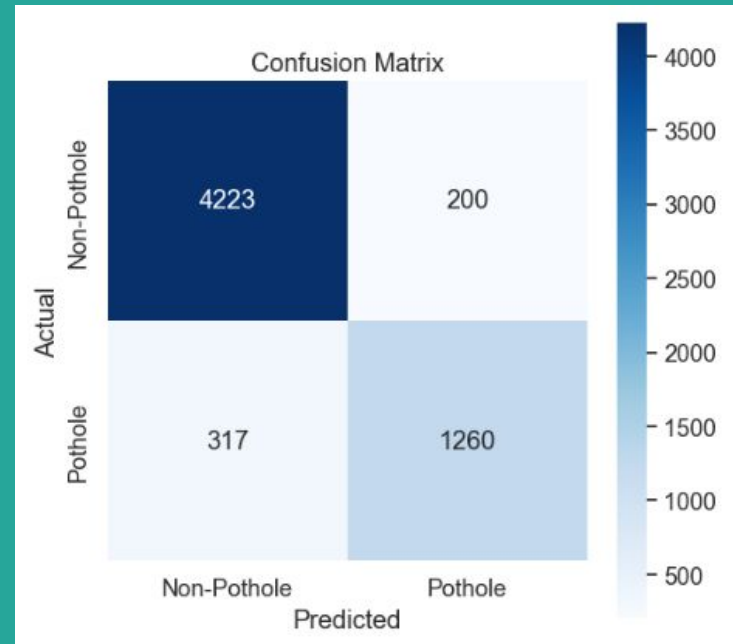
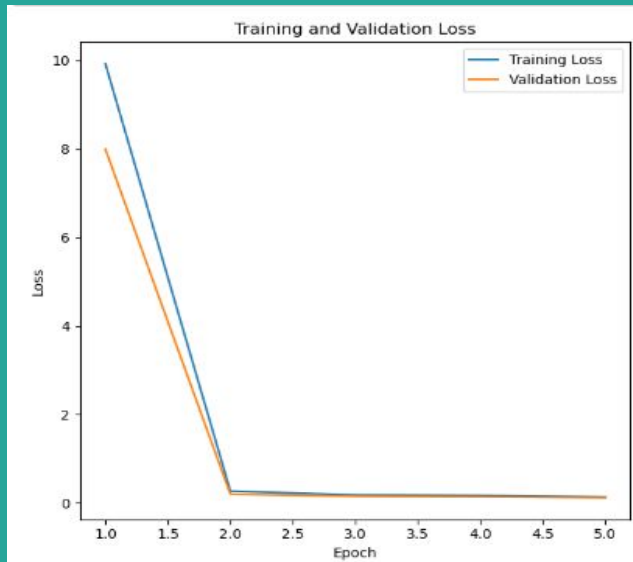
# Our chosen Model

## Convolutional Neural Network

CNN models are ideal for image classification tasks like this

Layer (type)	Output Shape	Param #
rescaling_9 (Rescaling)	(None, 32, 32, 3)	0
conv2d_27 (Conv2D)	(None, 32, 32, 128)	3584
batch_normalization_9 (Batch Normalization)	(None, 32, 32, 128)	512
activation_9 (Activation)	(None, 32, 32, 128)	0
max_pooling2d_27 (MaxPooling2D)	(None, 16, 16, 128)	0
conv2d_28 (Conv2D)	(None, 14, 14, 256)	295168
max_pooling2d_28 (MaxPooling2D)	(None, 7, 7, 256)	0
conv2d_29 (Conv2D)	(None, 5, 5, 512)	1180160
max_pooling2d_29 (MaxPooling2D)	(None, 2, 2, 512)	0
flatten_9 (Flatten)	(None, 2048)	0
dense_18 (Dense)	(None, 512)	1049088
dropout_9 (Dropout)	(None, 512)	0
dense_19 (Dense)	(None, 4)	2052
Total params: 2530564 (9.65 MB)		
Trainable params: 2530308 (9.65 MB)		
Non-trainable params: 256 (1.00 KB)		

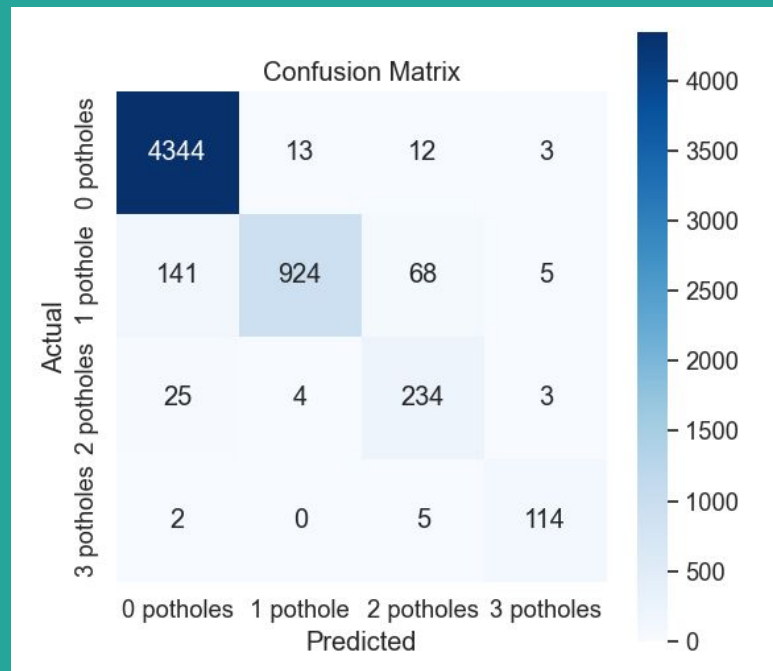
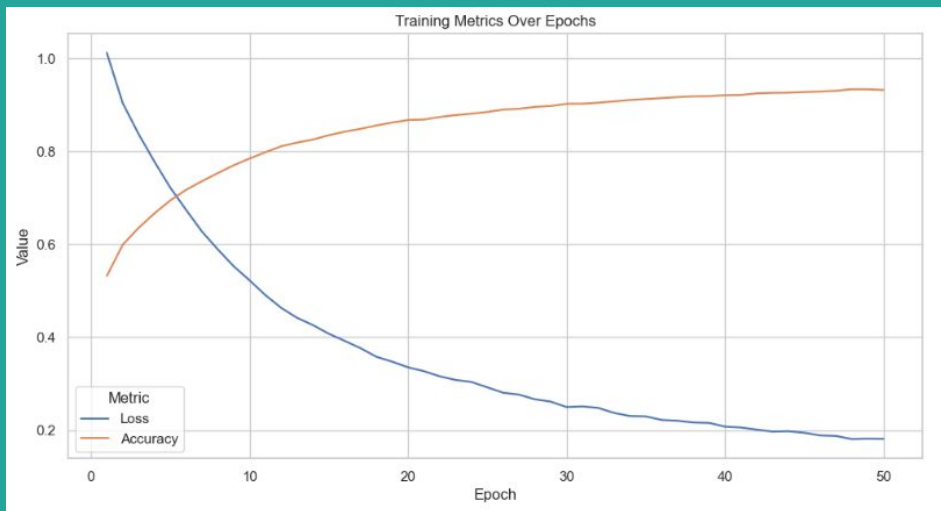
# Our binary results:



Roc\_Auc:92%



# Our multiclass results:

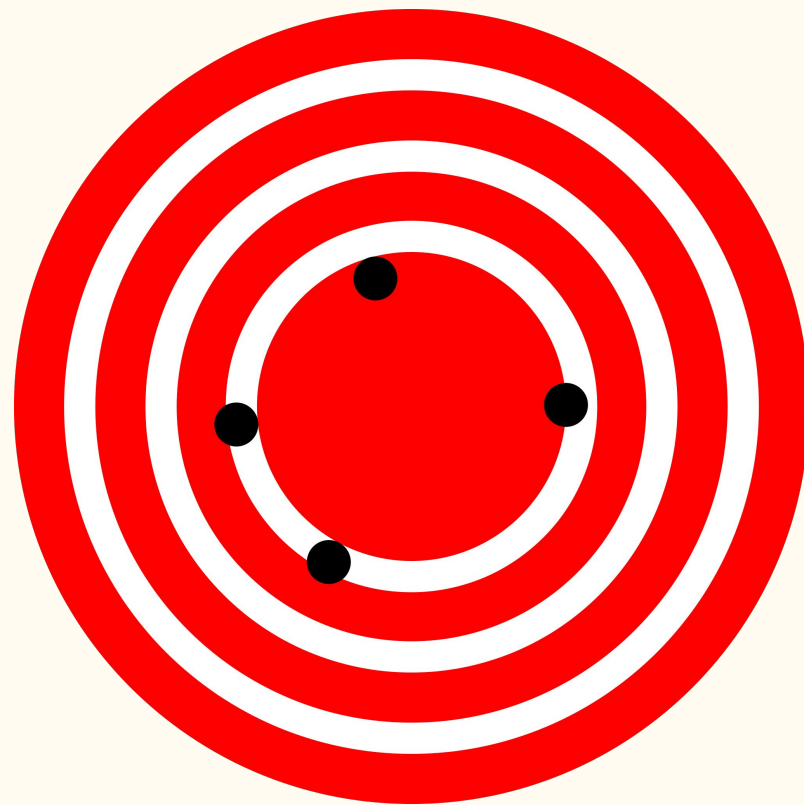


Roc\_Auc: 0.9616

# Why we chose our metrics

AUC-ROC (Area Under the Curve of the Receiver Operating Characteristic)

- It handles imbalanced classes better.
- AUC-ROC looks at both sensitivity and specificity, giving a better idea of how well our model can tell classes apart.



# Conclusion

1. - Successfully developed a deep learning model for pothole detection, achieving a significant roc\_auc score of 96% on the test dataset.
2. - Overcame challenges in data preprocessing, class imbalance, and model optimization through collaborative problem-solving.
3. - The model demonstrated robust performance in accurately identifying potholes, with a decreasing loss and increasing accuracy over 50 epochs.

# Next Step

4. - Transfer learning models may have even better results due to their diversity in training
5. - Explore opportunities to collaborate with local authorities for real-world implementation of the pothole detection system.
  - Investigate the integration of additional features, such as road quality assessment and anomaly detection.