

# Chip Happens:

## A Machine Learning Approach for Detecting Potato Chip Defects

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Nick Hay • 16.02.2024  
Capstone Project



# Bio

Nicholas Hay

Education: Bachelor of Technology Degree in Food Science (2000)

Professional experience: Food manufacturing, Insurance, Bookkeeping

Data Science learnings: Data Science & AI Bootcamp (IOD)

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# Agenda

- Opportunity
  - Data
  - Modelling
  - Results
  - Deployment
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Can image recognition & machine learning classify potato chips as defective (or non defective)

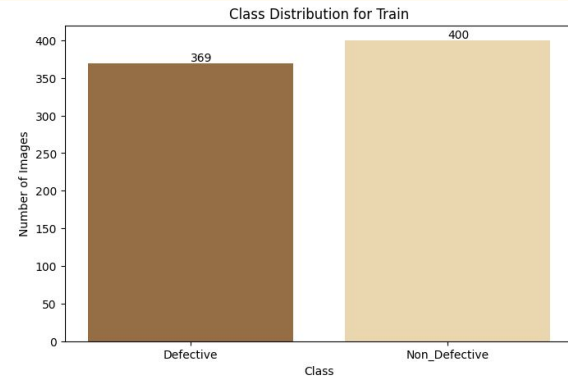
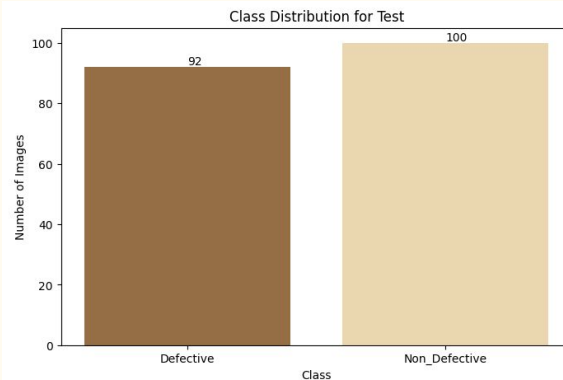


# Data Analysis

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# Data / EDA

- Sourced from Kaggle [1]
- 961 images
- Labelled (Train / Test)
  - Test, Defective - 92 images
  - Test, Not Defective - 100 images
  - Train, Defective - 369 images
  - Train, Non Defective - 400 images
- Size - Original 2976, resized 224
- Manipulated



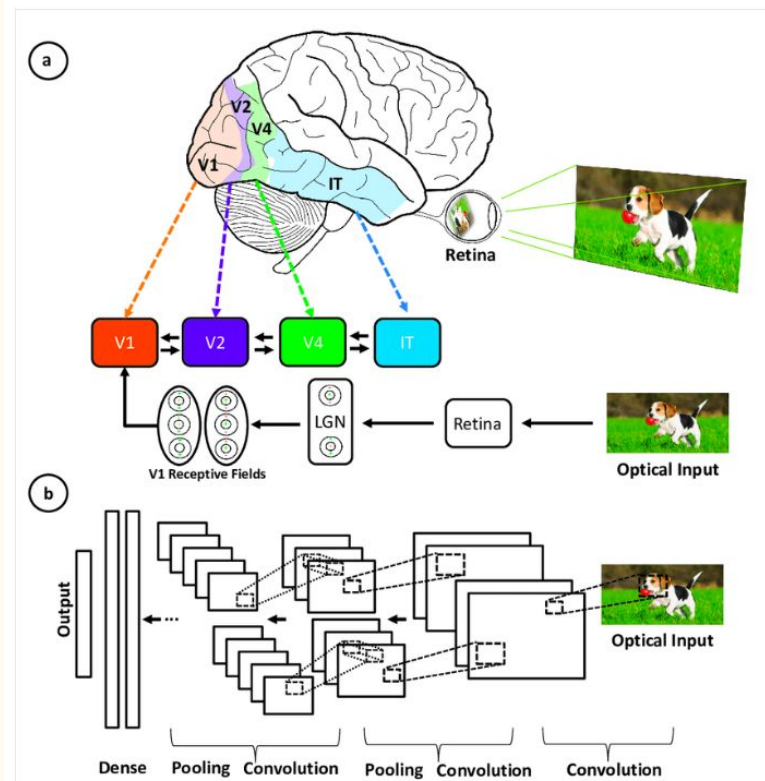
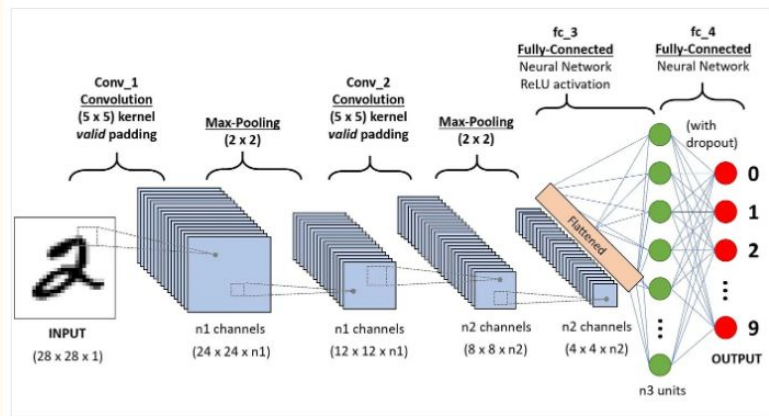
# Modelling

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# Convolutional Neural Network (CNN) [2]

## Key Components of CNN:

- Convolutional layers
- Activation function - Rectified Linear Unit (ReLU)
- Pooling layers
- Fully connected layers





# Sequential Model (Binary Classification)

- Import the images (Image Data Generator) can augment (transform by flipping, shifts)
- Load Data (flow from directory)
- Normalise image pixels (divide by 255)
- Construct model architecture (add layers)
  - Convolution (2D)
  - Max Pooling
  - Flatten
  - Dense
- Train the model (pre-trained VGG19, ResNet50)
- Evaluate the model
- Made predictions

## Hyperparameters

**Image Size:** 224 x 224

**Batch Size:** 32 images

**Epochs:** Number of Passes (10 - 30)

**Early Stopping:** Patience (3) on Validation Loss

**Validation Split:** 20% of Training data

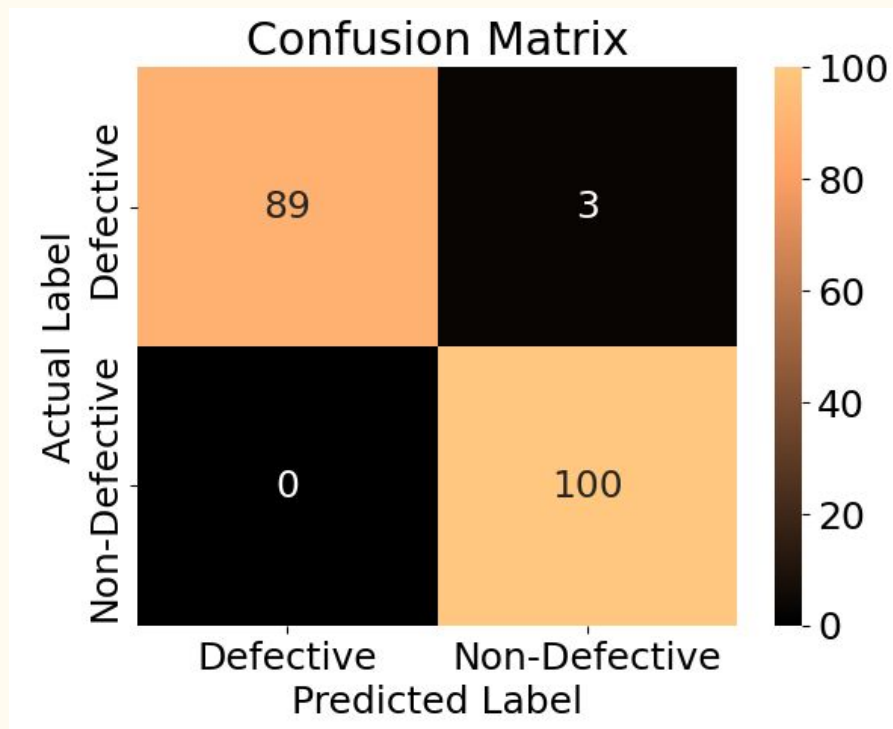
# Results

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# Results:

Model	Training Accuracy	Validation Accuracy	Accuracy on Evaluation
First attempt	100%	99%	98.44%
VGG19	100%	99%	98.44%
ResNet50	100%	52%	52.08%
First attempt (Augmented)	100%	100%	98.96%

# VGG19 - Confusion Matrix



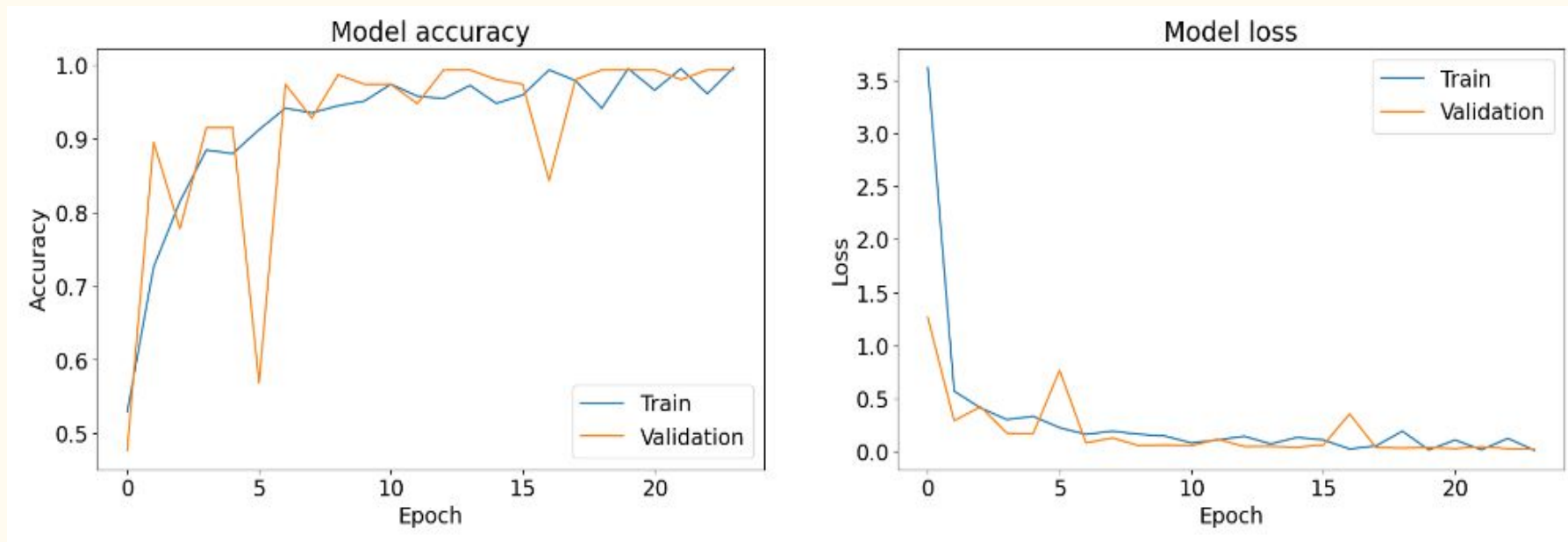
**True Positives (TP):** The model correctly predicted 89 defective items.

**True Negatives (TN):** The model correctly predicted 100 non-defective items.

**False Negatives (FN):** The model incorrectly predicted 3 defective items as non-defective.

**False Positives (FP):** The model did not make any incorrect predictions of non-defective items as defective.

# VGG19 - Model Accuracy & Loss



# VGG19 Predictions



Predicted: Defective  
Actual: Defective



Predicted: Defective  
Actual: Defective



Predicted: **\*\*Non Defective\*\* (incorrect)**  
Actual: Defective



Predicted: Defective  
Actual: Defective



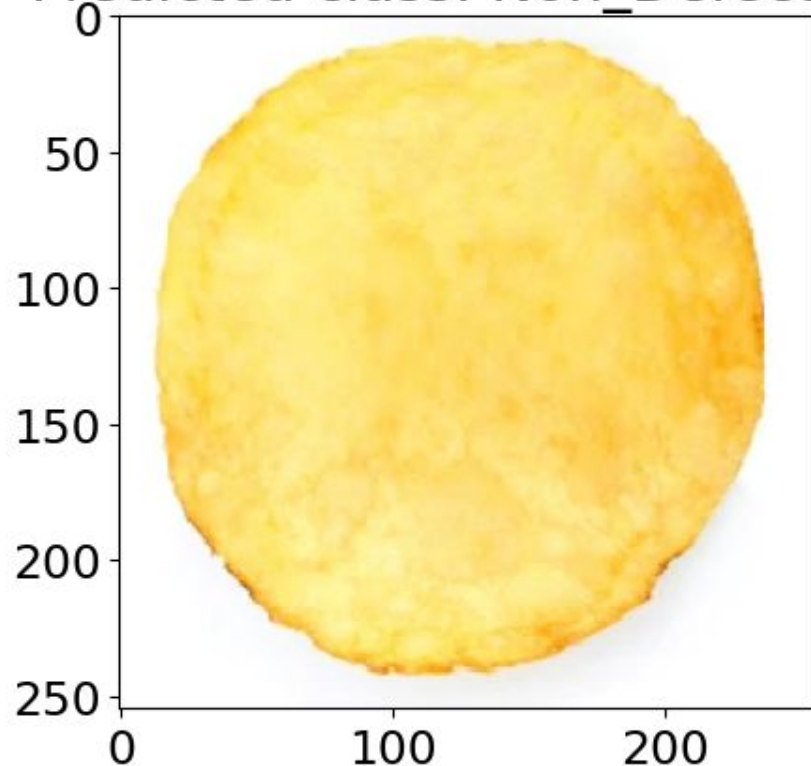
Predicted: Defective  
Actual: Defective



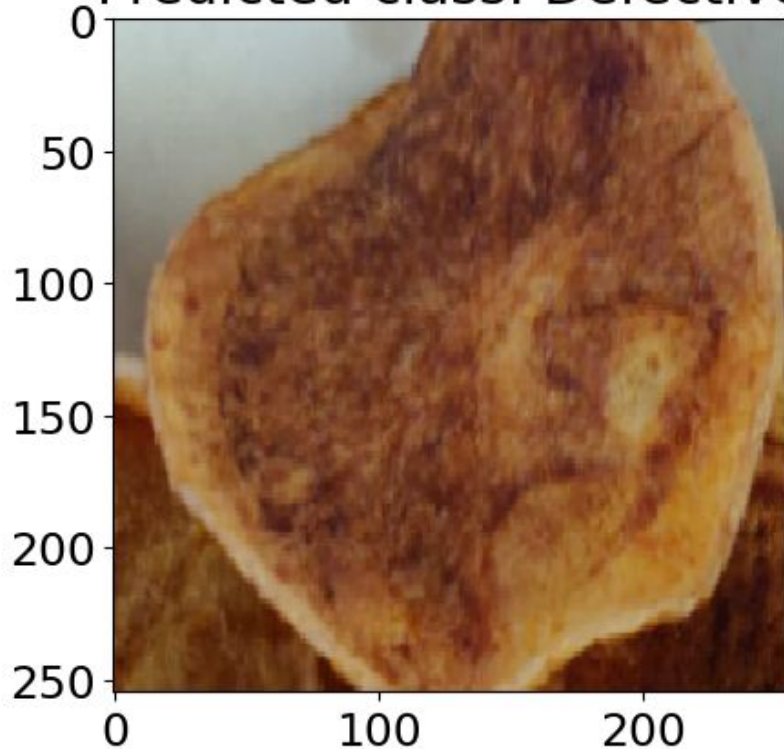
Predicted: Defective  
Actual: Defective

# VGG19 - Correct Predictions

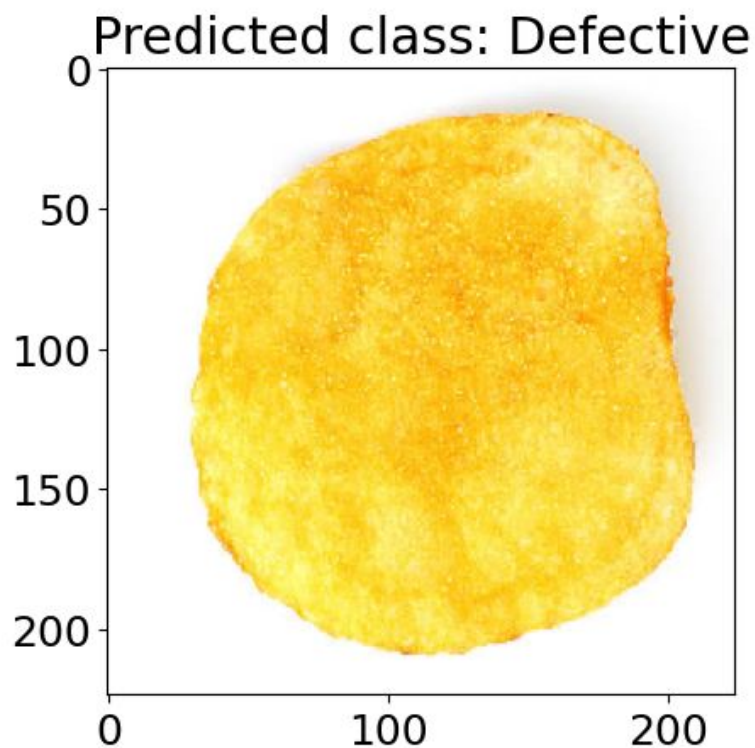
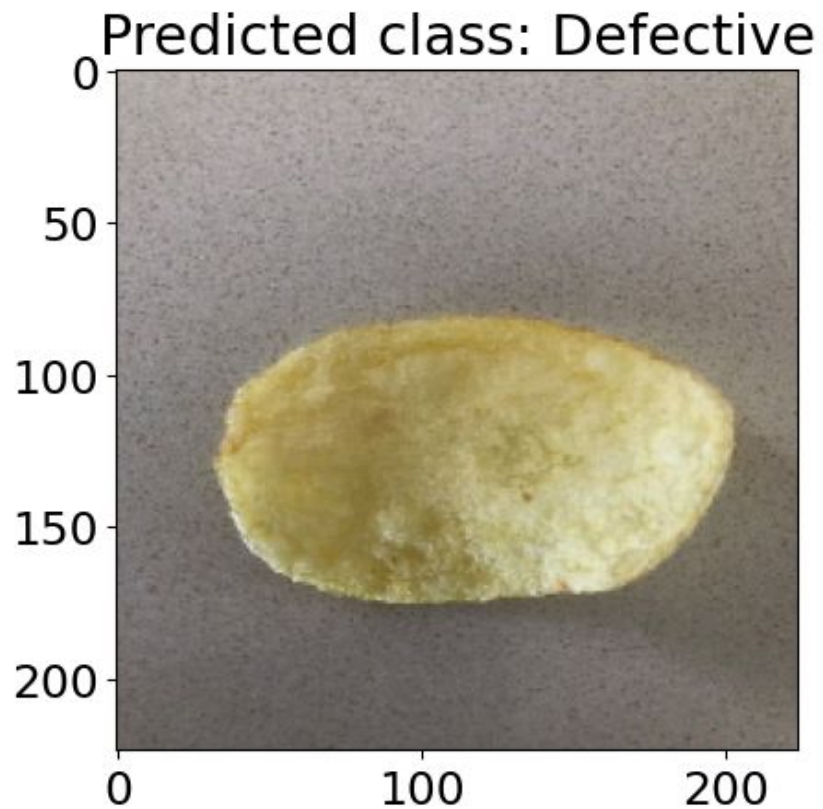
Predicted class: Non\_Defective



Predicted class: Defective



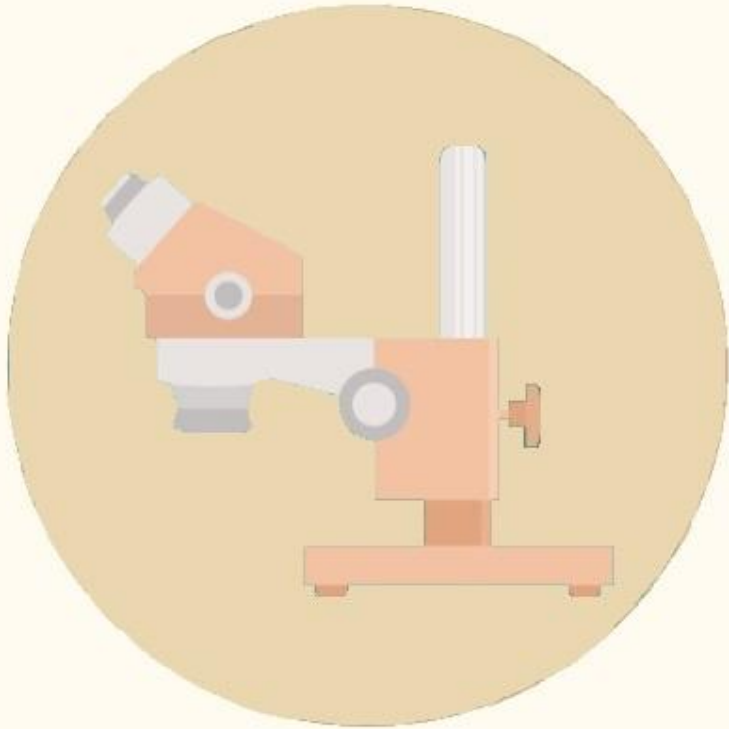
# VGG19 - Incorrect Predictions





# Implementation

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Deployment - Application



# Conclusion & Future work

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# Conclusion & Future Work

- Machine learning can predict defective images
- Application to verify the model is working
- Train the model using more images
- Computing power to run more epochs
- Techniques to minimise overfitting
- Recommend to stakeholders, investigate the practical implications of deploying the model in a manufacturing environment.



**Thank you  
&  
Questions**

# References:

[ 1 ] Navid, Usama. “PepsiCo Lab Potato Chips Quality Control.” *Kaggle*,  
<https://www.kaggle.com/datasets/concaption/pepsico-lab-potato-quality-control>

[ 2 ] Keita, Zoumana. “An Introduction to Convolutional Neural Networks: A Comprehensive Guide to CNNs in Deep Learning.” *DataCamp*, <https://www.datacamp.com/tutorial/introduction-to-convolutional-neural-networks-cnns>.

