Earthquake Damage Assessment

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I Problem Statement

- The April 2015 Nepal earthquake (also known as the Gorkha earthquake) killed 8,962 people

- It occurred on Saturday 25 April 2015, with a magnitude of 7.8Mw and a maximum Mercalli Intensity of X (Extreme).

- This led to an urgency in requirement of solution for similar events

- The need for an automated system is born which can reduce human effort

II INTRODUCTION

- In this mini project, we propose an innovative approach to damage severity assessment system using Convolutional Neural Networks (CNN) and Image Classification Using BigTransfer (BiT) networks.

- Our goal is to develop a robust system that can accurately identify and classify severity of damages from images by leveraging the power of deep learning.

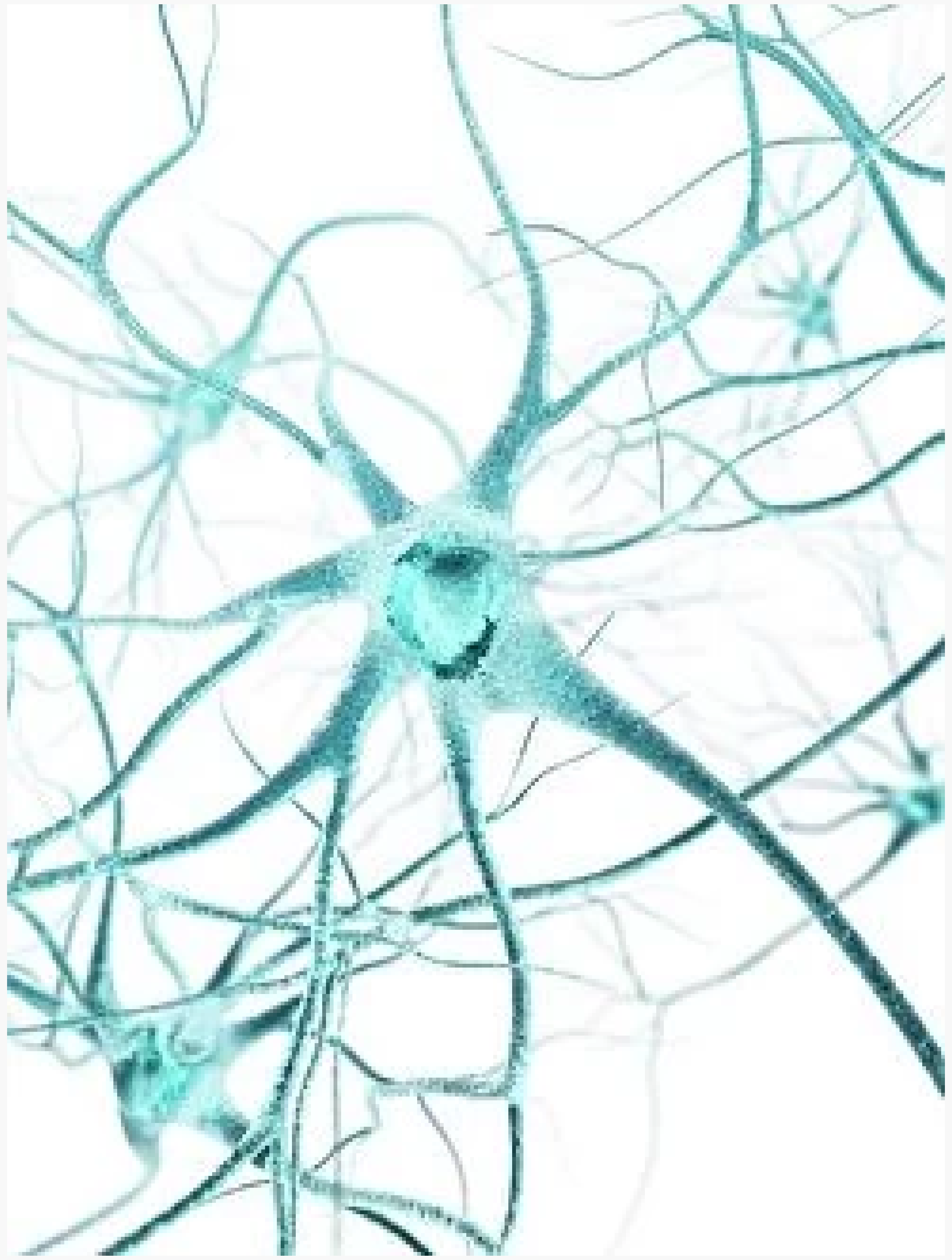
Rapid Assessment

- Rapid damage assessment is a task that humanitarian organizations perform within the first 48 to 72 hours of a disaster.
- Traditional ways to perform rapid damage assessment require sending experts to the disaster affected area to collect information.
- Such challenges can delay data gathering thus affecting lives of the people in distress.

III Neural Networks

What is neural network?

- Neural networks are a type of artificial intelligence
- They consist of interconnected nodes or neurons organized into layers.
- Each neuron receives an input signal, processes the signal using an activation function, and produces an output signal.

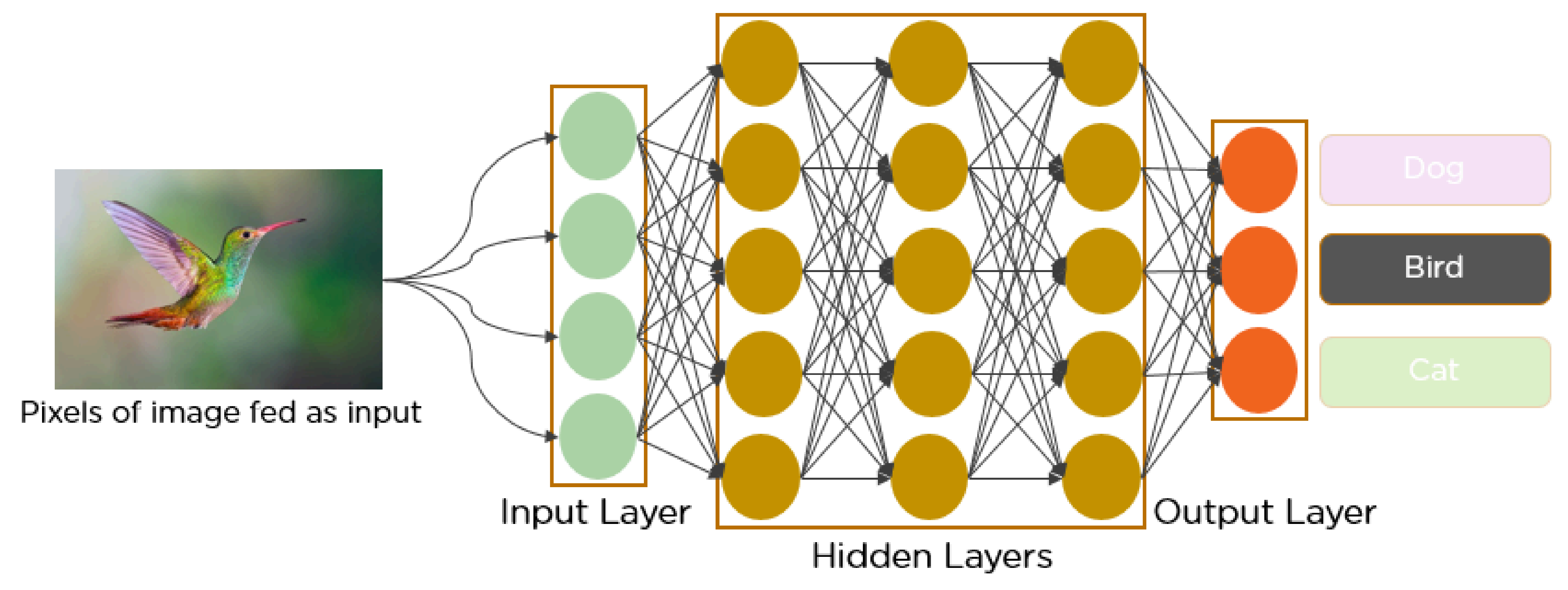


III Neural Networks

There is one particular type of Neural Network that we are interested in

- Convolution Neural Network (CNNs)

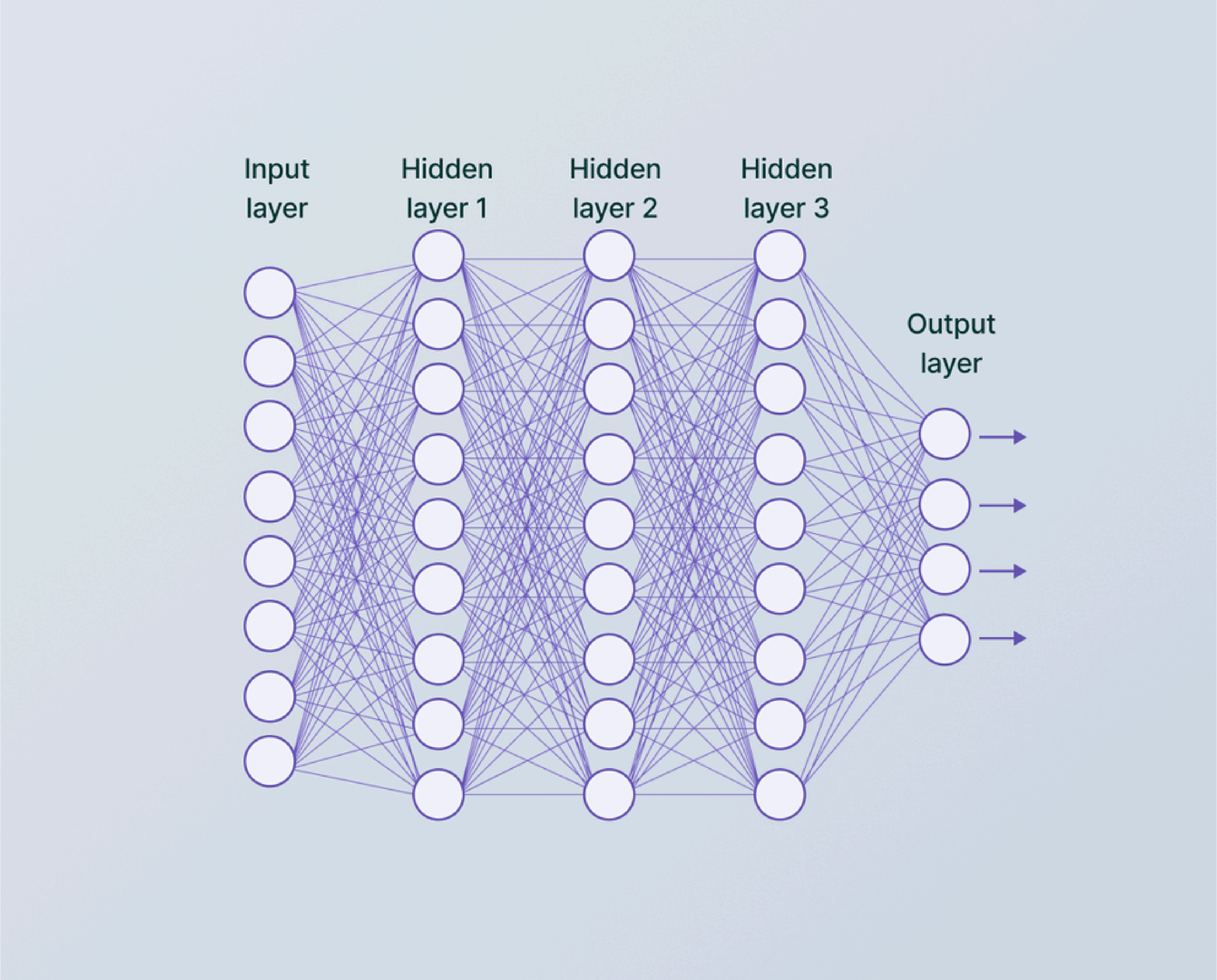
CNNs are good at identifying patterns and features in images.



III Neural Networks

Convolution Neural Networks (CNNs)

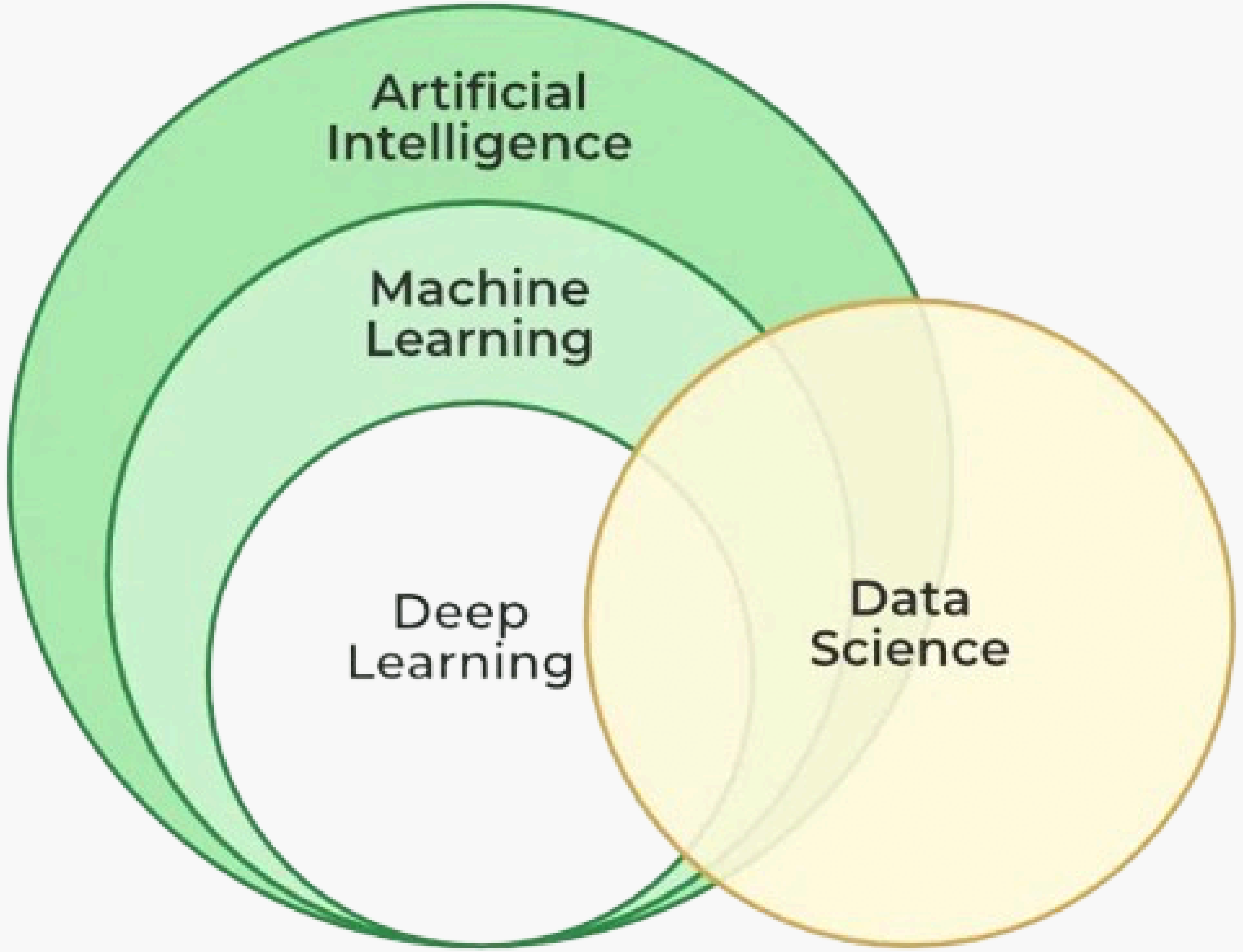
- CNN stands for Convolutional Neural Network.
- It is a type of artificial neural network commonly used in image recognition and computer vision tasks.
- CNNs take inspiration from animal visual processing systems.

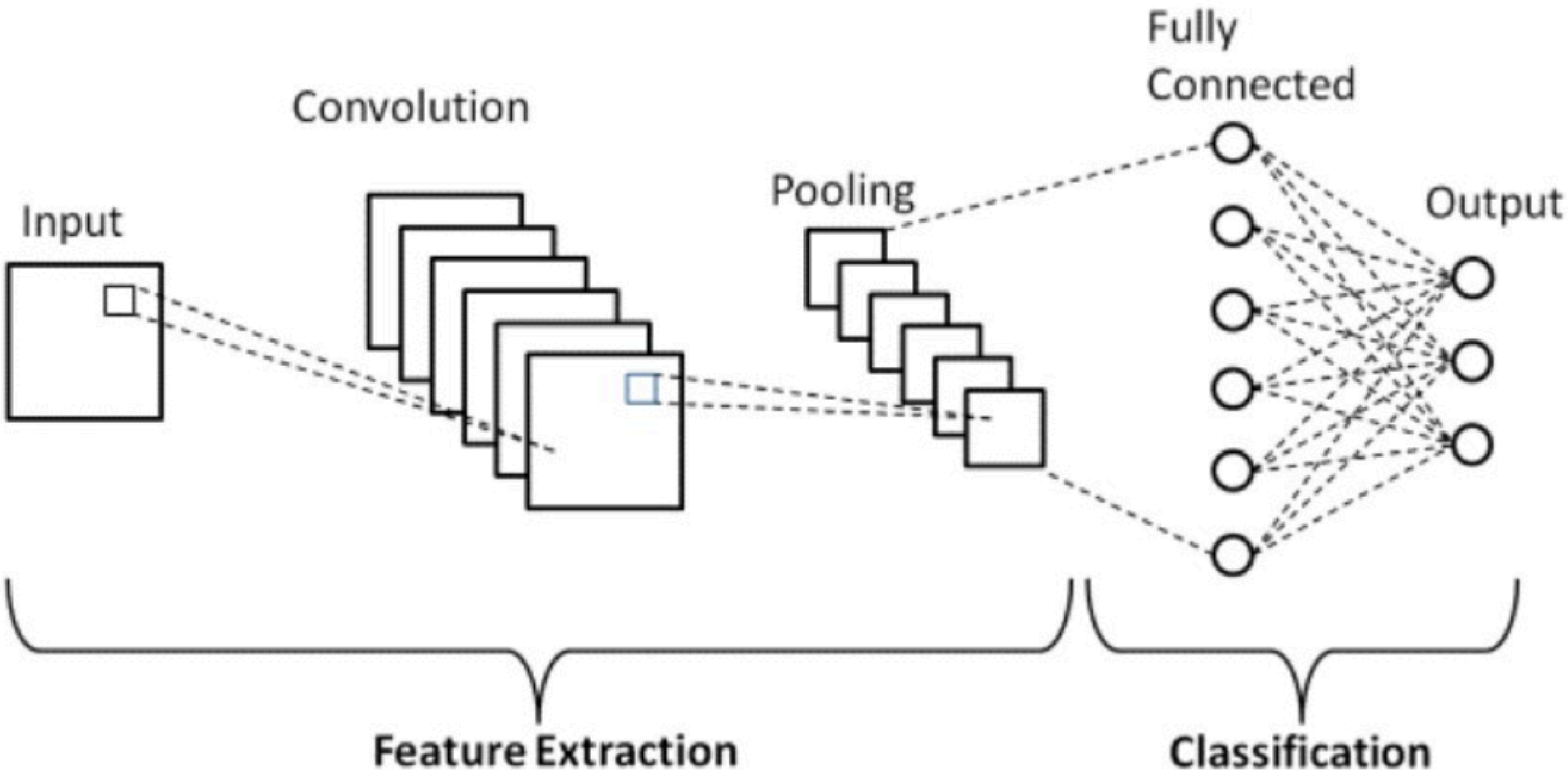


III Neural Networks

Components of CNN

- **Convolutional layers:**
- **Pooling Layers**
- **Activation Function**
- **Fully Connected Layers**





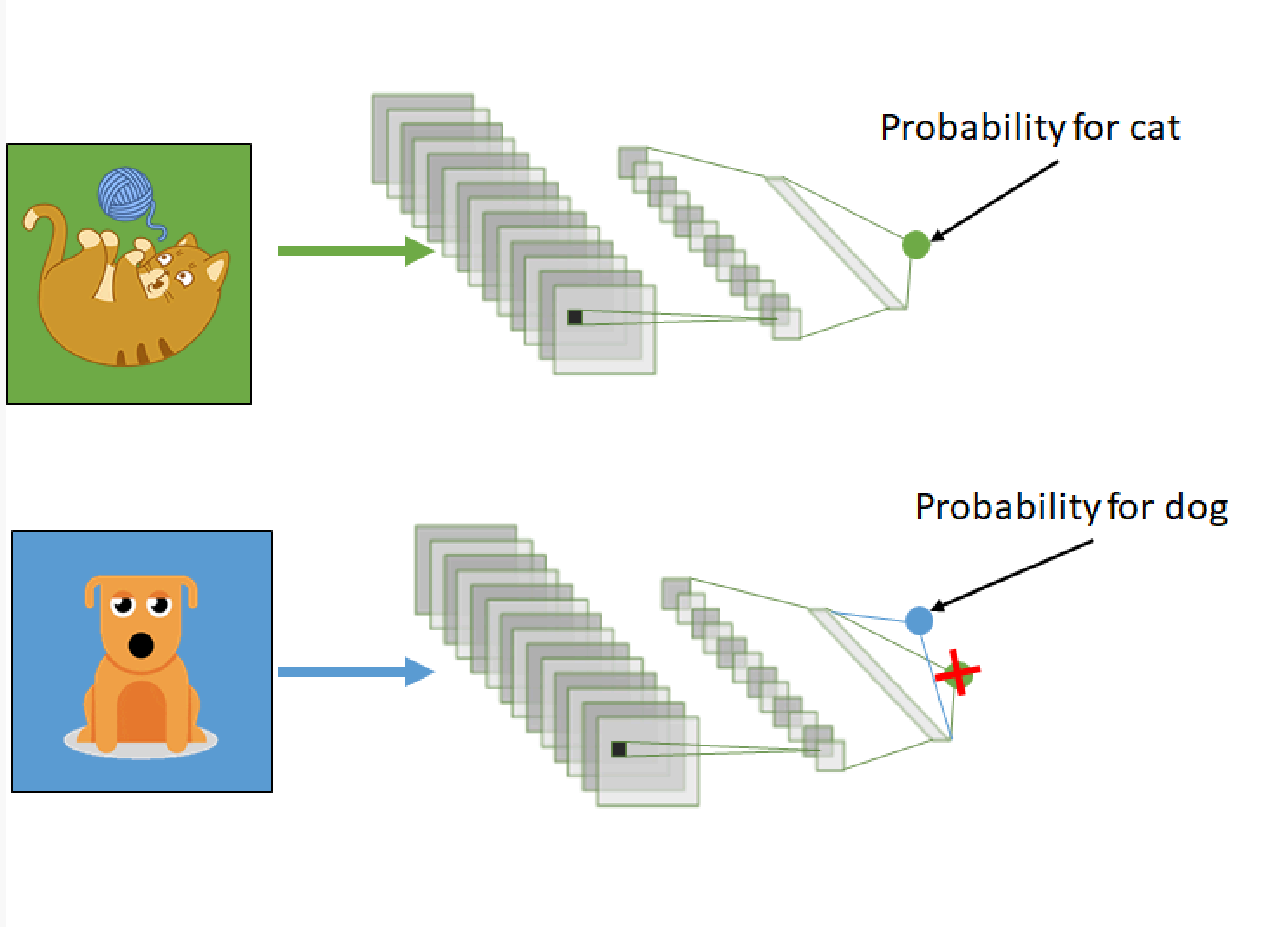
CNN : Convolutional Neural Network

III Neural Networks

Image Classification using BigTransfer (BiT)

- state-of-the-art transfer learning method for image classification.

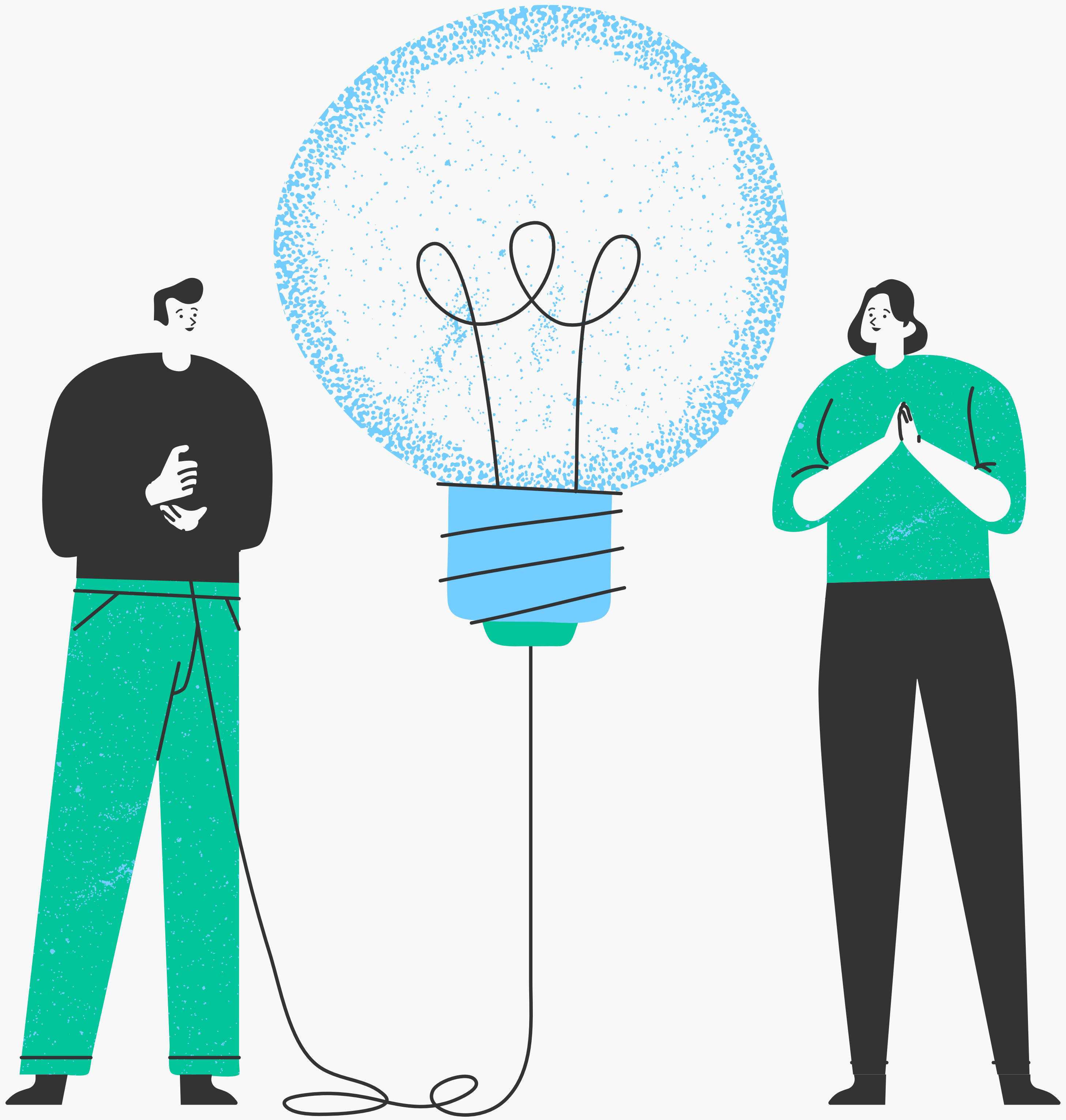
- Transfer of pre-trained representations improves sample efficiency.



III Neural Networks

How does BiT work?

- State-of-the-Art Transfer Learning
- Normalization Layer Selection
- Architecture Scaling
- Accessibility



IV Methodology

Part 1: Dataset Collection

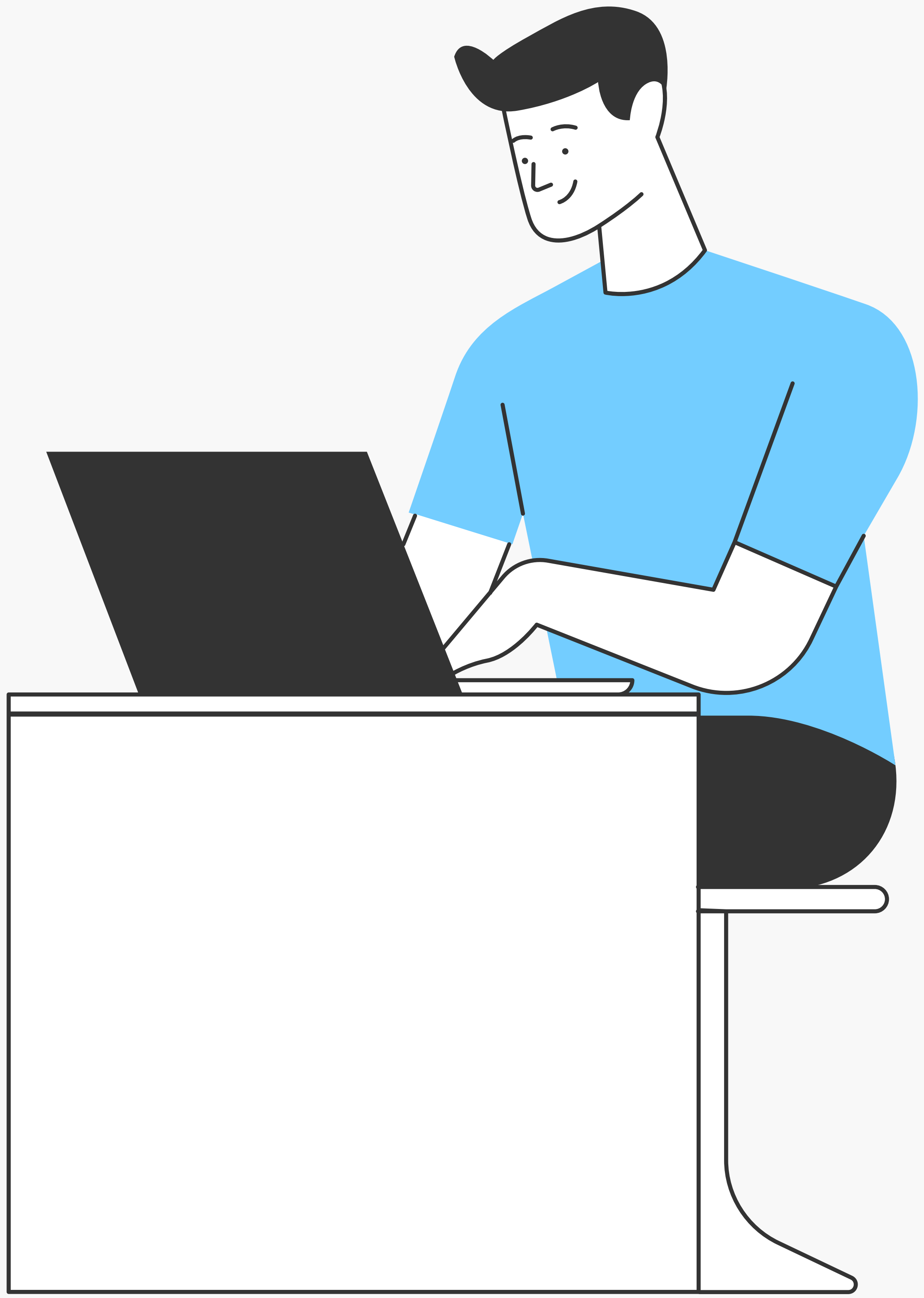
This study uses the social media dataset. The dataset includes images of Nepal Earthquake Disaster dataset. The dataset included images with three different class information:

1. Severe Damage
2. Mild Damage
3. Little to No Damage

IV Methodology

Part 2: Pre-Processing

1. We will convert the images into the size of (128 * 128 * 3)
2. 3 represents the RGB component of the image
3. (128 * 128) represents the height and width of the image.
4. The pixel values of the images are normalized in the range 0-1 by dividing each pixel value by 255.



IV Methodology

Part 3: Implementing the Model

3.1 Using CNN:

Once the CNN architecture is defined, the model is trained using the Adam optimizer with categorical cross-entropy loss. The training data, consisting of

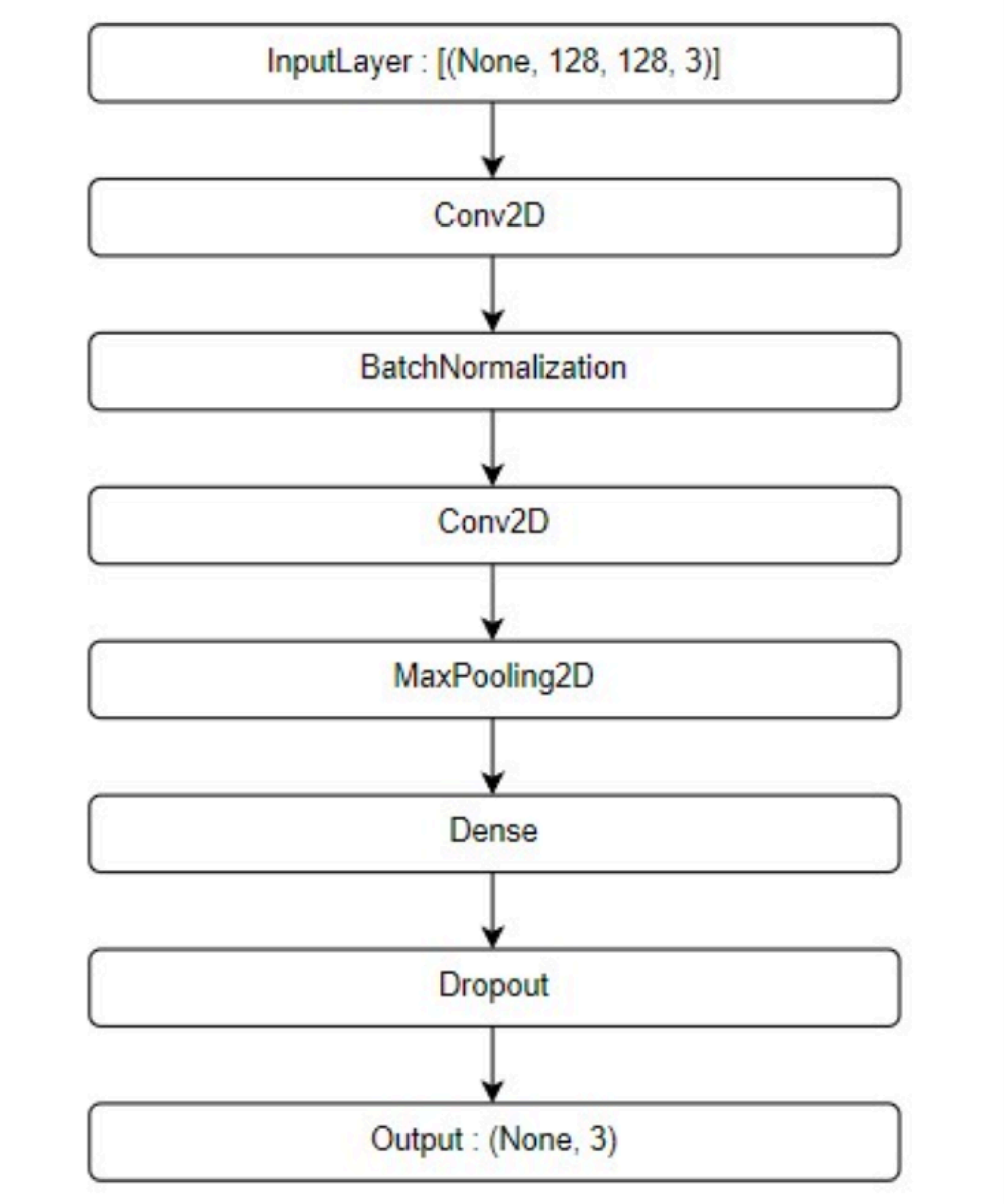
1. MaxPooling Layers
2. Dropout Layers
3. Flattening Layer
4. Fully Connected layers
5. Output Layer

IV Methodology

Construction of the Model

We have used:

- 8 Conv2D layers
- 4 MaxPooling layers
- 4 Dropout Layers
- 2 Dense Layers



IV Methodology

Part 3: Implementing the Model

3.2 using BiT:

- BigTransfer (also known as BiT) is a state-of-the-art transfer learning method for image classification

- Transfer of pretrained representations improves sample efficiency and simplifies hyperparameter tuning when training deep neural networks for vision.

IV Methodology

Model Integration

1. We define an input layer with shape (224, 224, 3) to match the input dimensions required by the BiT model.
2. The output from the BiT model is obtained by passing the input layer through the BiT model, and then, we add a dense output layer with softmax activation to classify images into three categories.
3. This output layer is responsible for making predictions based on the features extracted by the BiT model.

V Result Analysis

- After training the CNN model the accuracy we get on training dataset is to be 96.68% and testing dataset is to be 82.28%.
- While using the BiT model , the accuracy we achieved on training dataset is 90.01% and on the testing dataset it is 84.48%.

	Training accuracy	Test accuracy
CNN Model	96.68%	82.28%
BiT Model	90.01%	84.48%

V Result Analysis

- Accuracy: Accuracy measures how well a machine learning model can correctly predict or classify a given set of data.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Precision: Precision is the percentage of true positive predictions.

$$Precision = \frac{TP}{TP + FP}$$

- Recall: Recall calculates the percentage of true positive predictions out of all actual positive cases in the data.

$$Recall = \frac{TP}{TP + FN}$$

V Result Analysis

CNN Model Result

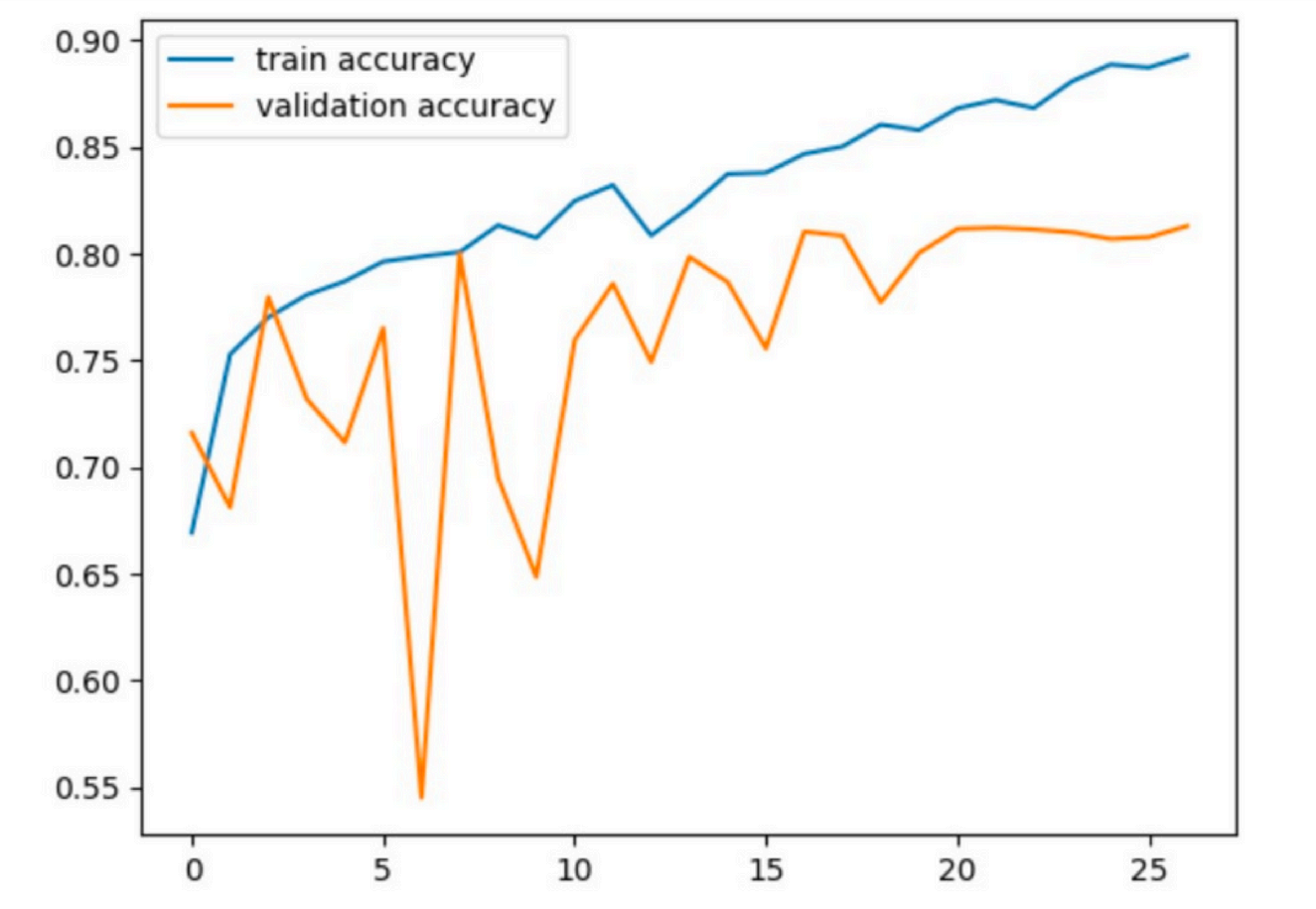
	precision	recall	f1-score	support
0	0.84	0.85	0.84	1584
1	0.47	0.29	0.37	451
2	0.86	0.92	0.88	1784
accuracy			0.82	3819
macro avg	0.71	0.68	0.69	3819
weighted avg	0.82	0.83	0.80	3819

BiT Model Result

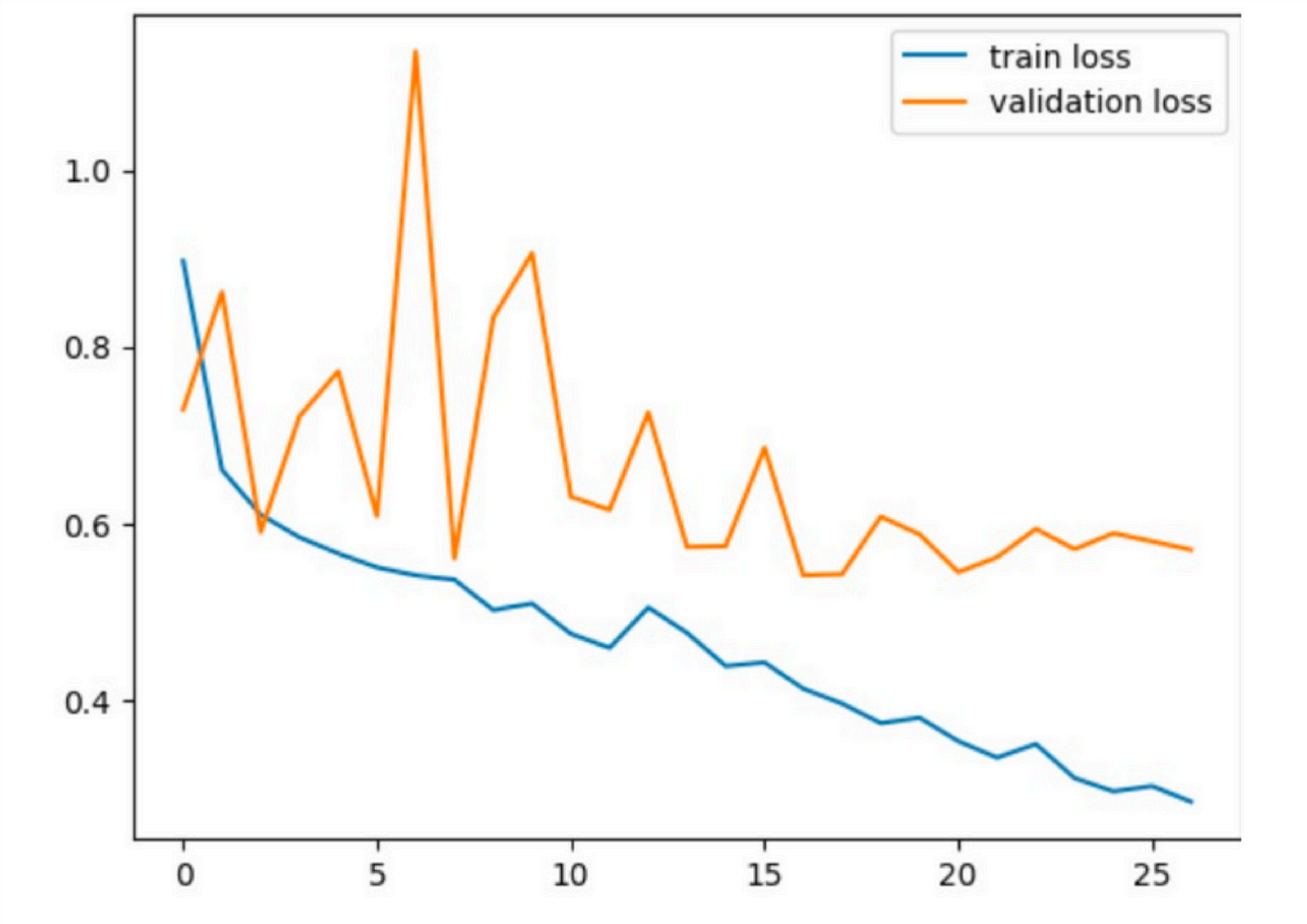
	precision	recall	f1-score	support
0	0.86	0.86	0.86	1584
1	0.48	0.29	0.36	451
2	0.86	0.95	0.90	1784
accuracy			0.84	3819
macro avg	0.71	0.67	0.68	3819
weighted avg	0.84	0.83	0.81	3819

V Result Analysis

Accuracy Curve

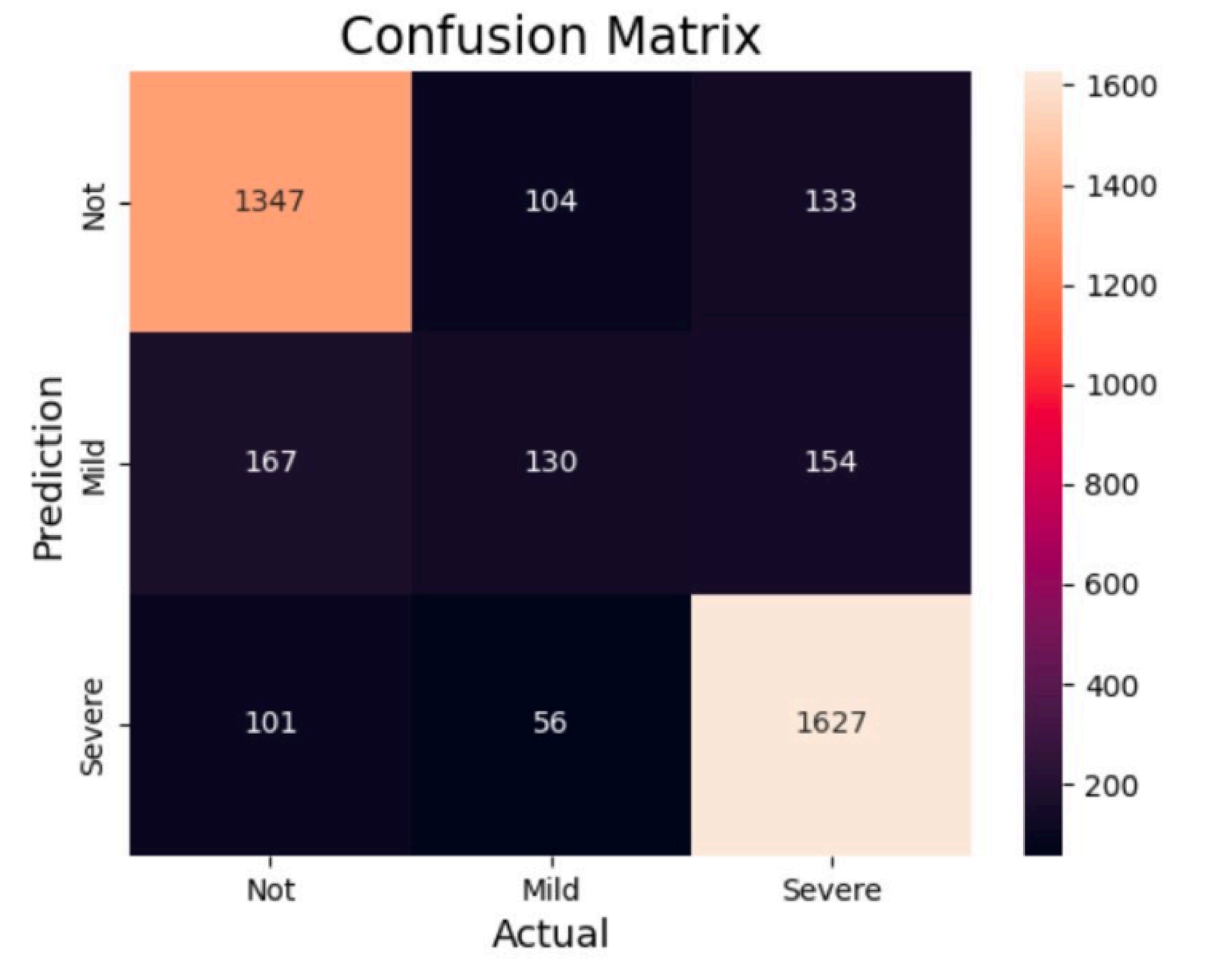


Loss Curve



V Result Analysis

Confusion Matrix: A confusion matrix is a tool in machine learning to measure the performance of a classification model.



VI Conclusion & Future Work

Conclusion

- Our research underscores the potential of machine learning in solving real-world challenges such as disaster damage assessment.
- By pushing the boundaries of model architecture we pave the way for more accurate, efficient, and accessible methods for understanding and interpreting human behaviour from visual data.
- This work not only contributes to the advancement of computer vision and machine learning but also holds implications for diverse applications

VI Conclusion & Future Work

Future Work

Integration of Drone Shot Images:

We intend to incorporate drone-shot images into our assessment framework. Drone imagery provides high-resolution, bird's eye views of disaster-affected areas, offering valuable insights into damage extent and severity.

Video Data Analysis:

We aim to develop machine learning models capable of analyzing video data to assess damage in realtime to support response and recovery efforts as soon as possible

Text-Based Damage Assessment:

Text data from social media posts, news articles, and other sources can provide valuable context and information about the impact of disasters. We plan to develop natural language processing (NLP) algorithms to analyze text data and extract relevant insights related to damage assessment.

VII References

1. Alam, F., Ofli, F., and Imran, M. (2018a). “CrisisMMD: Multimodal twitter datasets from natural disasters”. English. In: Proc. of the 12th ICWSM, 2018. AAAI press, pp. 465–473.
2. Attari, N., Ofli, F., Awad, M., Lucas, J., and Chawla, S. (2017). “Nazr-CNN: Fine-Grained Classification of UAV Imagery for Damage Assessment”. In: 2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA), pp. 50–59.
3. Zhang, Y., Yang, Q.: A survey on multi-task learning. IEEE Transactions on Knowledge and Data Engineering (2021)
4. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large- scale image recognition. arXiv preprint arXiv:1409.1556 (2014)
5. Worsham, J., Kalita, J.: Multi-task learning for natural language process- ing in the 2020s: where are we going? Pattern Recognition Letters 136, 120–126 (2020)