PYTHON-BASED DEEP LEARNING FOR IMAGE CLASSIFICATION

INTERNSHIP REPORT

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BACHELOR OF TECHNOLOGY

in

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By

PRIYANSHU NIRANJAN [21CS1034]

Internship work at

DATA PATTERNS (INDIA) PVT. LTD., CHENNAI - 603 103
Under the external guidance of
Linto Thomas, Associate Manager, Data Patterns

PUDUCHERRY TECHNOLOGICAL UNIVERSITY

(An Autonomous Institution of Govt. of Puducherry)

(Erstwhile Pondicherry Engineering College)

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This is to certify that the dissertation work entitled **"PYTHON-BASED DEEP LEARNING FOR IMAGE CLASSIFICATION"** was carried out by PRIYANSHU NIRANJAN bearing registration number 21CS1034 in partial fulfillment of the requirements for the degree of Bachelor of Technology in Computer Science and Engineering of the Puducherry Technological University, during the academic year 2023-24 is a bonafide record of work carried out under our guidance and supervision.

The results embodied in this report have not been submitted to any other University or Institution for the award of any degree or diploma.

Dr. M. Thenmozhi	**Dr. G. Zayaraz**
Associate-Professor	**Professor**
Internal-Guide	**HOD-CSE**

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DATA PATTERNS

Dated: Jan 2024

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This is to certify that **PRIYANSHU NIRANJAN (21CS1034) Puducherry Technological University (PTU)** has undergone internship training from 21 December 2023 to 07 January 2024 in the Data Patterns (India) Ltd., Chennai - 603 103. The project **"PYTHON-BASED DEEP LEARNING FOR IMAGE CLASSIFICATION"** is a record of the bonafide work undertaken by him towards partial fulfillment of the requirements for the award of the Degree of B.Tech (Bachelor of Technology) in CSE (Computer Science and Engineering) from**.** He has completed the assigned task satisfactorily.

(LINTO THOMAS)	(K.V. MUNI PRASAD)	(KARTHICK)
Associate Manager-SDG	Manager-SDG	Sr. Manager
Guide	Group Director	HRD
Data Patterns, Chennai	Data Patterns, Chennai	Data Patterns, Chennai

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DECLARATION

I hereby declare that the results embodied in this dissertation titled **"PYTHON-BASED DEEP LEARNING FOR IMAGE CLASSIFICATION"** is carried out by me during the year 2023-24 in partial fulfillment of the award of B.Tech (Bachelor of Technology) in CSE (Computer Science and Engineering) from **"Puducherry Technological University (PTU), Puducherry".** I have not submitted the same to any other university or organization for the award of any other degree.

Priyanshu Niranjan
21CS1034, CSE
PTU, Puducherry

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ABSTRACT

This report explores the application of Python in deep learning for image classification. It delves into various deep learning algorithms, emphasizing the importance of algorithm selection for image classification tasks. The top ten widely used deep learning algorithms, including Convolutional Neural Networks (CNNs) and Autoencoders, are presented.

The report then discusses the dataset used for training and testing the image classification model. It provides insights into the intricacies of loading and preprocessing image data, showcasing code snippets using the Keras library for practical implementation.

A crucial aspect of the report lies in the presentation and analysis of results obtained from training the deep learning model on the chosen dataset. The model's performance and accuracy in image classification are thoroughly examined, offering insights into the efficacy of the chosen algorithm and Python-based implementation.

To ensure academic rigor, the report includes a comprehensive list of citations and references, serving as a valuable resource for readers interested in further exploration of the discussed theories, algorithms, and Python libraries.

The code implementation seamlessly integrates practical snippets, bridging the gap between theoretical concepts and real-world application. From loading and preprocessing data using gzip to utilizing TensorFlow and Keras for building the image classification model, the code walkthrough provides a tangible understanding of the implementation process.

In conclusion, this report serves as a holistic guide to employing Python-based deep learning for image classification. By combining theoretical discussions, practical code implementation, and insightful analysis of results, it caters to a diverse audience of researchers, practitioners, and enthusiasts. The emphasis on algorithm selection, dataset considerations, and Python programming nuances fosters a deeper understanding of the symbiotic relationship between Python and deep learning in the context of image classification.

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CONTENTS

CHAPTER-1
Introduction

1.1 Overview

Classification is a systematic arrangement of groups and categories based on their features. Image classification began to decrease the gap between computer vision and human vision by training the computer with the data. The image classification is achieved by differentiating the image into the prescribed category based on the content of the vision.

Machine Learning is the science of getting computers to learn without being explicitly programmed. It is closely related to computational statistics, which focuses on making prediction using computer. In its application across business problems, machine learning is also referred as predictive analysis. Machine Learning is closely related to computational statistics. Machine Learning focuses on the development of computer programs that can access data and use it to learn themselves. The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly

Deep learning is a method in artificial intelligence (AI) that teaches computers to process data in a way that is inspired by the human brain. Deep learning models can recognize complex patterns in pictures, text, sounds, and other data to produce accurate insights and predictions. You can use deep learning methods to automate tasks that typically require human intelligence, such as describing images or transcribing a sound file into text.

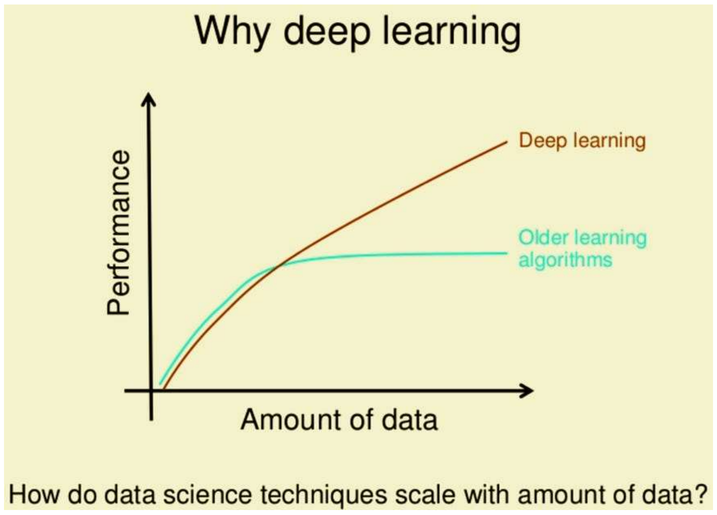

Figure 1.1: Deep Learning Algorithms Performance over amount of data

1.2 Understanding the Mechanisms of Machine Learning

Machine learning is the concept that a computer program can learn and adapt to new data without human interference. Machine learning is a field of artificial intelligence (AI) that keeps a computer's built-in algorithms current regardless of changes in the worldwide economy. Machine learning algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as in medicine, email filtering, speech recognition, and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.

Machine Learning is complex, which is why it has been divided into two primary areas, supervised learning and unsupervised learning. Each one has a specific purpose and action, yielding results and utilizing various forms of data. Approximately 70 percent of machine learning is supervised learning, while unsupervised learning accounts for anywhere from 10 to 20 percent. The remainder is taken up by reinforcement learning.

1.2.1 Supervised Learning

In supervised learning, we use known or labeled data for the training data. Since the data is known, the learning is, therefore, supervised, i.e., directed into successful execution. The input data goes through the Machine Learning algorithm and is used to train the model. Once the model is trained based on the known data, you can use unknown data into the model and get a new response.

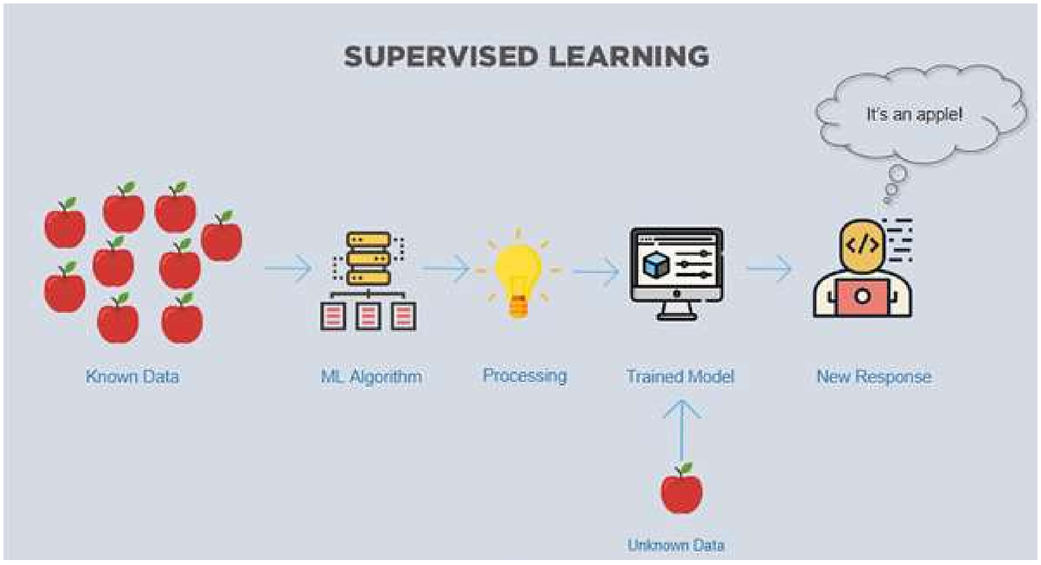

Figure 1.1 Supervised Learning in Machine Learning

In this case, the model tries to figure out whether the data is an apple or another fruit. Once the model has been trained well, it will identify that the data is an apple and give the desired response.

Here is the list of top algorithms currently being used for supervised learning are:

- Polynomial regression
- Random forest
- Linear regression
- Logistic regression
- Decision trees
- K-nearest neighbors
- Naive Bayes

1.2.2. Unsupervised Learning

In unsupervised learning, the training data is unknown and unlabeled - meaning that no one has looked at the data before. Without the aspect of known data, the input cannot be guided to the algorithm, which is where the unsupervised term originates from. This data is fed to the Machine Learning algorithm and is used to train the model. The trained model tries to search for a pattern and give the desired response. In this case, it is often like the algorithm is trying to break code like the Enigma machine but without the human mind directly involved but rather a machine.

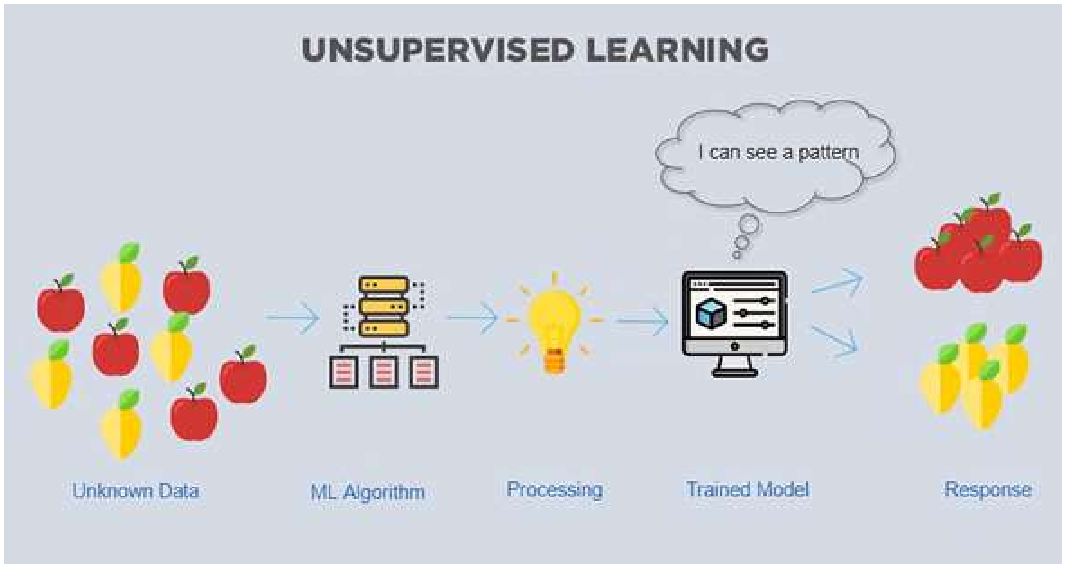

Figure 1.2: Unsupervised Learning in Machine Learning

In this case, the unknown data consists of apples and pears which look similar to each other. The trained model tries to put them all together so that you get the same things in similar groups.

The top algorithms currently being used for unsupervised learning are:

- Partial least squares
- Fuzzy means
- Singular value decomposition
- K-means clustering
- Apriori
- Hierarchical clustering
- Principal component analysis

1.2.3. Reinforcement Learning

Like traditional types of data analysis, here, the algorithm discovers data through a process of trial and error and then decides what action results in higher rewards. Three major components make up reinforcement learning: the agent, the environment, and the actions. The agent is the learner or decision-maker, the environment includes everything that the agent interacts with, and the actions are what the agent does.

Reinforcement learning happens when the agent chooses actions that maximize the expected reward over a given time. This is easiest to achieve when the agent is working within a sound policy framework.

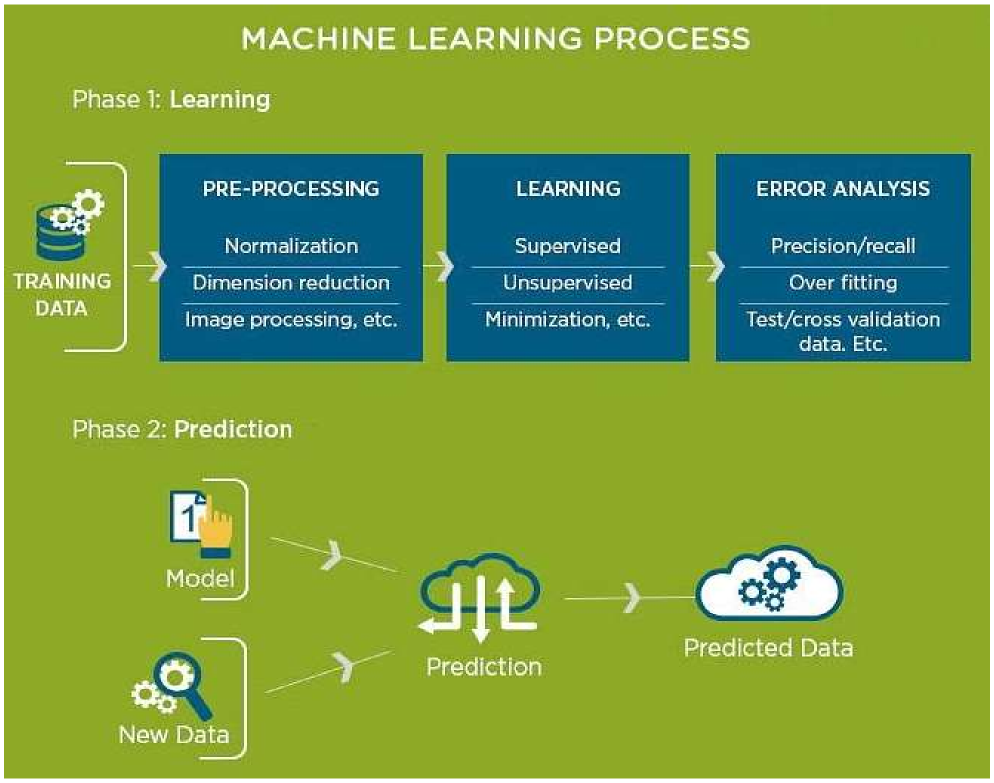

Figure 1.3: General Machine Learning Procedure

1.3 Understanding the Mechanisms of Deep Learning

Deep learning algorithms are neural networks that are modelled after the human brain. For example, a human brain contains millions of interconnected neurons that work together to learn and process information. Similarly, deep learning neural networks, or artificial neural networks, are made of many layers of artificial neurons that work together inside the computer.

Artificial neurons are software modules called nodes, which use mathematical calculations to process data. Artificial neural networks are deep learning algorithms that use these nodes to solve complex problems.

1.3.1 Components of a Deep Learning Network

The components of a deep neural network are the following.

1. **Input layer**

An artificial neural network has several nodes that input data into it. These nodes make up the input layer of the system.

2. **Hidden layer**

The input layer processes and passes the data to layers further in the neural network. These hidden layers process information at different levels, adapting their behavior as they receive new information. Deep learning networks have hundreds of hidden layers that they can use to analyze a problem from several different angles.

For example, if you were given an image of an unknown animal that you had to classify, you would compare it with animals you already know. For example, you would look at the shape of its eyes and ears, its size, the number of legs, and its fur pattern. You would try to identify patterns, such as the following:

- The animal has hooves, so it could be a cow or deer.
- The animal has cat eyes, so it could be some type of wild cat.

The hidden layers in deep neural networks work in the same way. If a deep learning algorithm is trying to classify an animal image, each of its hidden layers processes a different feature of the animal and tries to accurately categorize it.

3. **Output layer**

The output layer consists of the nodes that output the data. Deep learning models that output "yes" or "no" answers have only two nodes in the output layer. On the other hand, those that output a wider range of answers have more nodes

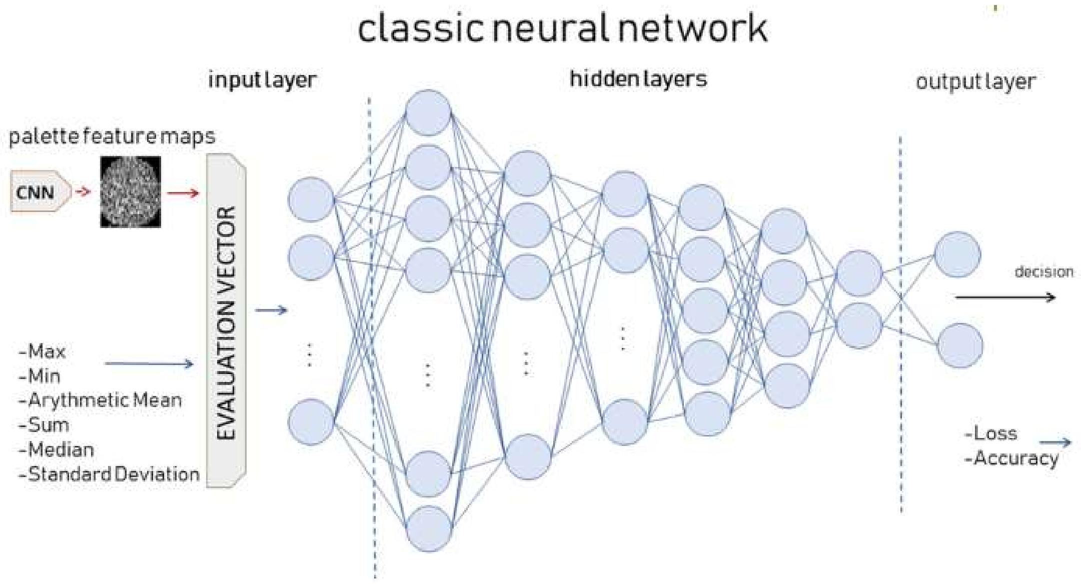

Figure 1.4: Classical Neural Network used in deep learning

1.4 Deep Learning Compared to Traditional Machine Learning

Deep learning is a subset of machine learning. Deep learning algorithms emerged in an attempt to make traditional machine learning techniques more efficient. Traditional machine learning methods require significant human effort to train the software. For example, in animal image recognition, you need to do the following:

- Manually label hundreds of thousands of animal images.
- Make the machine learning algorithms process those images.
- Test those algorithms on a set of unknown images.
- Identify why some results are inaccurate.
- Improve the dataset by labeling new images to improve result accuracy.

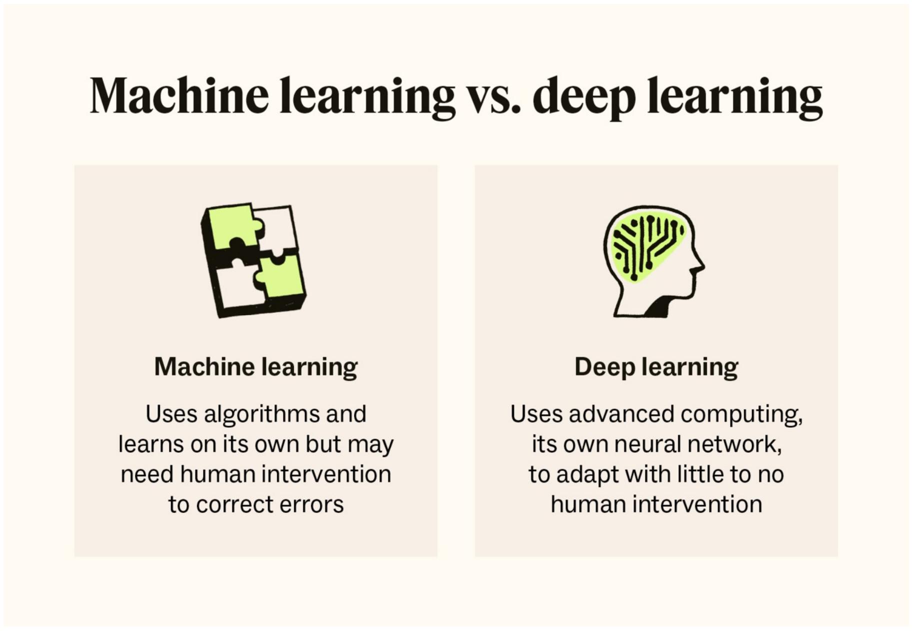
Machine learning vs. deep learning
Machine learning
Uses algorithms and learns on its own but may need human intervention to correct errors
Deep learning
Uses advanced computing, its own neural network, to adapt with little to no human intervention

Figure 1.5: Machine Learning and Deep Learning Methodologies

This process is called supervised learning. In supervised learning, result accuracy improves only when you have a broad and sufficiently varied dataset. For instance, the algorithm might accurately identify black cats but not white cats because the training dataset had more images of black cats. In that case, you would need to label more white cat images and train the machine learning models once again.

1.4.1 Benefits of deep learning over machine learning

A deep learning network has the following benefits over traditional machine learning.

1. **Efficient processing of unstructured data**

Machine learning methods find unstructured data, such as text documents, challenging to process because the training dataset can have infinite variations. On the other hand, deep learning models can comprehend unstructured data and make general observations without manual feature extraction. For instance, a neural network can recognize that these two different input sentences have the same meaning:

- Can you tell me how to make the payment?
- How do I transfer money?

2. **Hidden relationships and pattern discovery**

A deep learning application can analyze large amounts of data more deeply and reveal new insights for which it might not have been trained. For example, consider a deep learning model that is trained to analyze consumer purchases. The model has data only for the items you have already purchased. However, the artificial neural network can suggest new items that you haven't bought by comparing your buying patterns to those of other similar customers.

3. **Unsupervised learning**

Deep learning models can learn and improve over time based on user behavior. They do not require large variations of labeled datasets. For example, consider a neural network that automatically corrects or suggests words by analyzing your typing behavior. Let's assume it was trained in the English language and can spell-check English words. However, if you frequently type non-English words, such as *danke*, the neural network automatically learns and autocorrects these words too.

4. **Volatile data processing**

Volatile datasets have large variations. One example is loan repayment amounts in a bank. A deep learning neural network can categorize and sort that data as well, such as by analyzing financial transactions and flagging some of them for fraud detection.

1.4.2 Challenges of a Deep Learning model

As deep learning is a relatively new technology, certain challenges come with its practical implementation.

1. **Large quantities of high-quality data**

Deep learning algorithms give better results when you train them on large amounts of high-quality data. Outliers or mistakes in your input dataset can significantly affect the deep learning process. For instance, in our animal image example, the deep learning model might classify an airplane as a turtle if non-animal images were accidentally introduced in the dataset.

To avoid such inaccuracies, you must clean and process large amounts of data before you can train deep learning models. The input data preprocessing requires large amounts of data storage capacity.

2. **Large processing power**

Deep learning algorithms are compute-intensive and require infrastructure with sufficient compute capacity to properly function. Otherwise, they take a long time to process results.

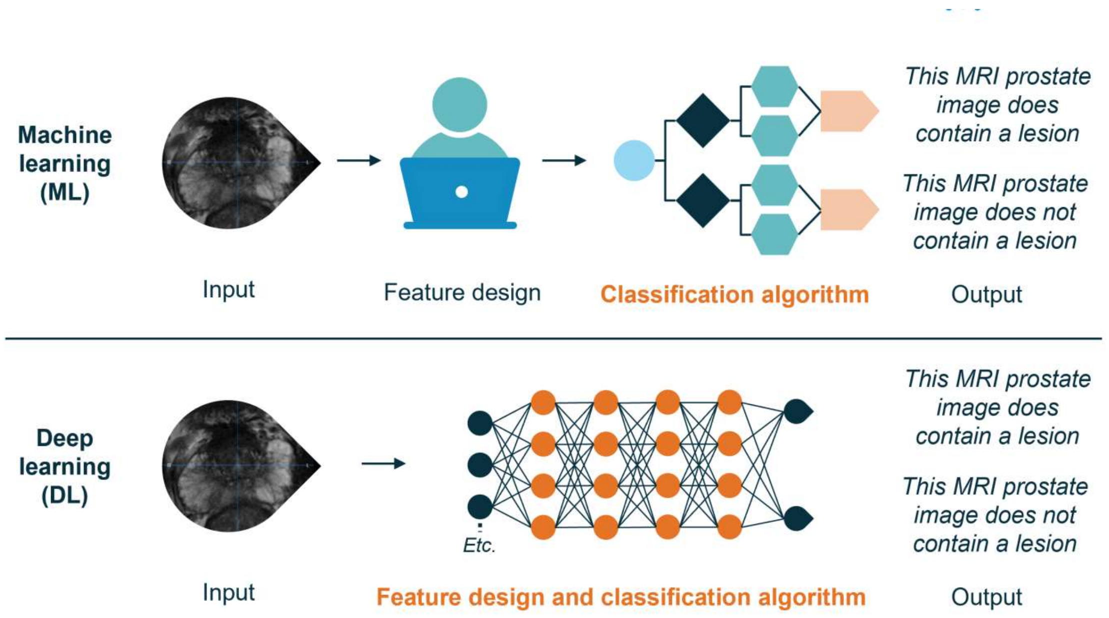
Machine learning (ML)
Input
Feature design
Classification algorithm
This MRI prostate image does contain a lesion
This MRI prostate image does not contain a lesion
Output
Deep learning (DL)
Input
Etc.
Feature design and classification algorithm
This MRI prostate image does contain a lesion
This MRI prostate image does not contain a lesion
Output

Figure 1.6: An MRI image being used to differentiate between Deep Learning and Machine Learning

1.5 Advancements through Deep Learning

Artificial intelligence (AI) attempts to train computers to think and learn as humans do. Deep learning technology drives many AI applications used in everyday products, such as the following:

- Digital assistants
- Voice-activated television remotes
- Fraud detection
- Automatic facial recognition

It is also a critical component of emerging technologies such as self-driving cars, virtual reality, and more.

Deep learning models are computer files that data scientists have trained to perform tasks using an algorithm or a predefined set of steps. Businesses use deep learning models to analyze data and make predictions in various applications.

Deep learning has several use cases in automotive, aerospace, manufacturing, electronics, medical research, and other fields. These are some examples of deep learning:

- Self-driving cars use deep learning models to automatically detect road signs and pedestrians.
- Defense systems use deep learning to automatically flag areas of interest in satellite images.
- Medical image analysis uses deep learning to automatically detect cancer cells for medical diagnosis.
- Factories use deep learning applications to automatically detect when people or objects are within an unsafe distance of machines.

You can group these various use cases of deep learning into four broad categories—computer vision, speech recognition, natural language processing (NLP), and recommendation engines.

Computer vision is the computer's ability to extract information and insights from images and videos. Computers can use deep learning techniques to comprehend images in the same way that humans do. Computer vision has several applications, such as the following:

- Content moderation to automatically remove unsafe or inappropriate content from image and video archives
- Facial recognition to identify faces and recognize attributes like open eyes, glasses, and facial hair
- Image classification to identify brand logos, clothing, safety gear, and other image details

Deep learning models can analyze human speech despite varying speech patterns, pitch, tone, language, and accent. Virtual assistants such as Amazon Alexa and automatic transcription software use speech recognition to do the following tasks:

- Assist call center agents and automatically classify calls.
- Convert clinical conversations into documentation in real time.
- Accurately subtitle videos and meeting recordings for a wider content reach.

Computers use deep learning algorithms to gather insights and meaning from text data and documents. This ability to process natural, human-created text has several use cases, including in these functions:

- Automated virtual agents and chat bots
- Automatic summarization of documents or news articles
- Business intelligence analysis of long-form documents, such as emails and forms
- Indexing of key phrases that indicate sentiment, such as positive and negative comments on social media

Applications can use deep learning methods to track user activity and develop personalized recommendations. They can analyze the behaviour of various users and help them discover new products or services. For example, many media and entertainment companies, such as Netflix, Fox, and Peacock, use deep learning to give personalized video recommendations.

1.6 Hardware Requirements

Deep learning requires a tremendous amount of computing power. High performance *graphical processing units (GPUs)* are ideal because they can handle a large volume of calculations in multiple cores with copious memory available. However, managing multiple GPUs on-premises can create a large demand on internal resources and be incredibly costly to scale.

CPUs are designed to run almost any calculation, that is why they are called general-purpose computers. In order to achieve this generality, CPUs store values in registers, while a program tells the Arithmetic Logic Units (ALUs) which registers to read, perform an operation (such as an addition, multiplication or logical AND) and which register to use for output storage, which in turn contains lots of sequencing of these read/operate/write operations. Due to this support for generality (registers, ALUs and programmed control), CPUs cost more in terms of power and chip area.

There are alternatives to the GPUs such as FPGAs and ASIC, as all devices do not contain the amount of power required to run a GPU (~450W, including CPU and motherboard). TPU (Tensor Processing unit) is another example of machine learning specific ASIC, which is designed to accelerate computation of linear algebra and specializes in performing fast and bulky matrix multiplications.

1.7 Evolution of Deep Learning over the years

The first step toward neural networks was taken in 1943, when Warren McCulloch, a neurophysiologist, and Walter Pitts, a young mathematician, published a paper on how neurons may work. They proposed an electrical circuit-based neural network. Donald Hebb proposed in1949 that brain connections became stronger with each usage. In the 1950s, IBM researcher Nathanial Rochester used IBM 704 computers to mimic abstract neural networks.

In 1956, four scientists collaborated on the Dartmouth Summer Research Project on Artificial Intelligence, which took place during the summer. John McCarthy, Marvin L. Minsky, Nathaniel Rochester, and Claude E. Shannon were the four scientists. They made a significant contribution to AI research. Following the Dartmouth study in 1957, John Von Neumann claimed that telegraph relays or vacuum tubes may be used to mimic the function of a single neuron. Frank Rosenblatt, a Cornell neurobiologist, began working on the Perceptron in 1958. He was enthralled by the activity of a fly's eye. In a fly's eye, a large part of the preparation that instructs it to flee is done. The Perceptron, which was developed as a result of this research, is the most well-known and widely used neural network today. A single layer perceptron was shown to be useful for classifying a single-valued collection of inputs into one of two categories. The perceptron calculates a weighted sum of the data sources, subtracts a limit, and outputs one of two possible qualities. Bernard Widrow and Marcian Hoff of Stanford developed the ADALINE and MADALINE 1 models in 1959. Multiple ADAptiveLINear Elements were used in these models, which gave them their moniker. MADALINE was the first neural network to be used to solve a problem in the real world. It's an adaptive channel for removing echoes from telephone lines. This neuronal structure is still used in the workplace. Surprisingly, these previous victories led people to exaggerate the capabilities of neural networks, especially given the hardware limitations at the time. The excessive excitement that emanated from the academic and technical disciplines poisoned the writing of the day. As promises were unfulfilled, disillusionment crept in. Similarly, as essayists considered the impact of "figuring machines" on a man, a sense of dread developed. Asimov's arrangement on robots revealed the implications for man's ethics and attributes when machines were capable of performing all of humanity's tasks. Interest in the field was reignited in 1982. Caltech's John Hopfield presented a paper to the National Academy of Sciences 2. His strategy was to use bidirectional wires to create more valuable devices. Previously, there was just one route for neurons to connect. A combined US-Japan Conference on Cooperative/Competitive Neural Networks was also held in 1982. Japan announced a new Fifth-Generation effort on neural networks, while US journals raised concerns that the US would be left behind in the sector (Fifth-Generation processing incorporates computerized reasoning). The first era used switches and wires, the second era used transistors, the third era used strong state technology such as integrated circuits and higher-level programming dialects, and the fourth era used code generators.) As a result, there was increased subsidizing and, as a result, more field exploration. The American Institute of Physics began a yearly conference called Neural Networks for Computing in 1985. The first

International Conference on Neural Networks, held by the Institute of Electrical and Electronics Engineers (IEEE) in 1987, gathered over 1,800 people. Schmidhuber and Hochreiter proposed the Long Short-Term Memory (LSTM) recurrent neural network structure in 1997. In the realm of deep learning, long momentary memory (LSTM) is an artificial recurrent neural network (RNN) architecture. LSTM has feedback connections, unlike normal feed forward neural networks. It not only cycles single information items (such as pictures), but also the entire stream of data (for example, speech or video). Yann LeCun released Gradient-Based Learning Applied to Document Recognition in 1998, which was a significant step forward in data learning.

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CHAPTER 2

Deep Learning Algorithms

2.1 Overview of Deep Learning Algorithms

Deep learning has exploded in prominence in scientific computing, with its techniques being utilized by a wide range of sectors to solve complicated issues. To perform certain tasks, all deep learning algorithms employ various forms of neural networks

While deep learning algorithms use self-learning representations, they rely on artificial neural networks (ANNs) that mimic how the brain processes information. Algorithms leverage unknown elements in the input distribution to extract features, organize objects, and uncover important data patterns throughout the training phase. This happens at various levels, employing the algorithms to develop the models, much like training machines for self-learning. Several algorithms are used in deep learning models. While no network is flawless, certain algorithms are better suited to specific jobs than others. To select the best, it's necessary to have a thorough understanding of all primary algorithms.

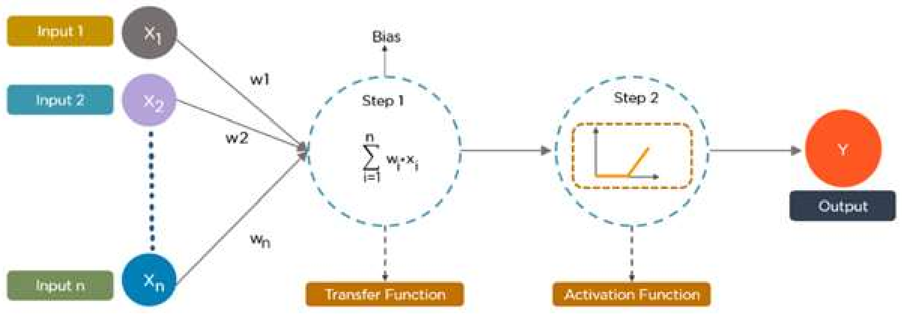

Figure 2.1: Deep Learning algorithms structure

2.2 An Insight into Deep Learning Algorithms

Deep learning algorithms can handle practically any type of data and require a lot of processing power and data to solve complex problems. Let's take a look at the top ten deep learning algorithms. The following is a list of the top ten most widely used deep learning algorithms:

1. Convolutional Neural Networks (CNNs)
2. Long Short-Term Memory Networks (LSTMs)

3. Recurrent Neural Networks (RNNs)
4. Restricted Boltzmann Machines (RBMs)
5. Autoencoders

2.2.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) CNNs, also known as ConvNets, are multilayer neural networks that are primarily used for image processing and object detection. In 1988, Yann LeCun created the first CNN, which he called LeNet. It could recognize characters such as ZIP codes and numerals. CNNs are commonly used to detect abnormalities, identify satellite photos, interpret medical imaging, forecast time series, and identify anomalies. Convolutional Neural Networks (CNN) are mostly employed in image processing. It assigns weights and biases to different items in the image and distinguishes them. In comparison to other classification methods, it requires less preparation. In order to capture the spatial and temporal dependencies in a picture, CNN employs relevant filters. LeNet, AlexNet, VG-GNet, GoogleNet, ResNet, and ZFNet are some of the different CNN architectures.

Object detection, semantic segmentation, and captioning are just a few of the applications that CNNs are utilized for. Multiple layers process and extract features from data in CNNs: CNN features a convolution layer that consists of many filters that perform the convolution operation. CNNs have a Rectified 6 Linear Unit (ReLU) layer that performs operations on elements. A rectified feature map is the result. The rectified feature map is fed into a pooling layer after that. Pooling is a down sampling procedure that decreases the feature map's dimensionality. By flattening the two-dimensional arrays from the pooled feature map, the pooling layer turns them into a single, long, continuous, linear vector. When the flattened matrix from the pooling layer is given as an input, a fully connected layer arises, which classifies and labels the images.

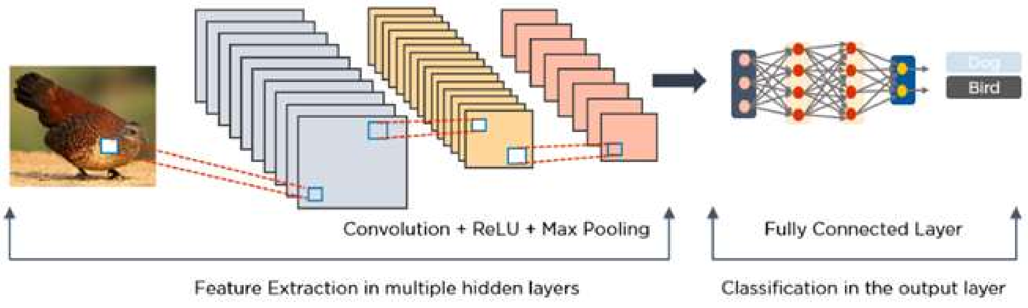
Dog
Bird
Convolution + ReLU + Max Pooling
Fully Connected Layer
Feature Extraction in multiple hidden layers
Classification in the output layer

Figure 2.2: Example of Convolutional Neural Networks (CNNs)

2.2.2. Long Short-Term Memory Networks (LSTMs)

Long Short-Term Memory Networks (LSTMs) Long-term dependencies can be learned and remembered using LSTMs [19], which are a form of Recurrent Neural Network (RNN). The default behavior is to recall past information over long periods of time. LSTMs keep track of data throughout time. Because they remember past inputs, they are valuable in time-series prediction.

Four interacting layers communicate in a unique way in LSTMs, which have a chain-like structure. LSTMs are commonly employed for voice recognition, music creation, and pharmaceutical research, in addition to time-series predictions. First, they forget about the portions of the previous state that aren't significant. They then update the cell-state values selectively. Finally, the state of some portions of the cell's output. Figure 2.2 is a diagram illustrating how LSTMs work.

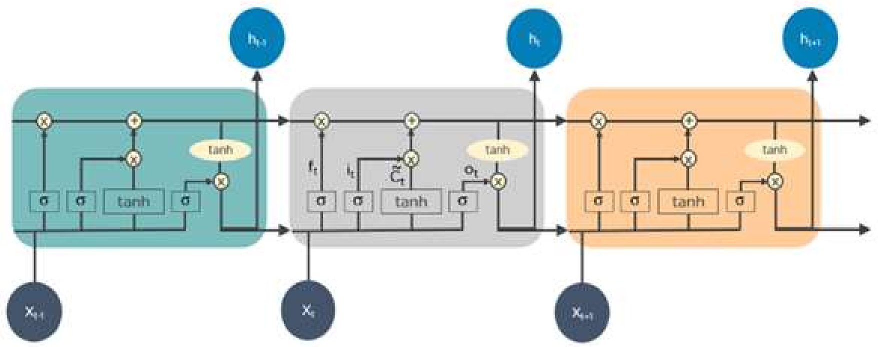

Figure 2.3: Long Short-Term Memory Networks (LSTMs)

2.2.3 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) The outputs from previous states are given as input to the present state in recurrent neural networks (RNN). RNN's hidden layers have the ability to remember information. The output created in the previous state is used to update the concealed state. RNN may be used to predict time series since it has Long Short-Term Memory, which allows it to remember prior inputs. The outputs from the LSTM can be given as inputs to the current phase since RNNs contain connections that create directed cycles. The

LSTM's output becomes an input to the current phase, and its internal memory allows it to remember prior inputs. Image captioning, time-series analysis, natural-language processing, handwriting identification, and machine translation are all common uses for RNNs. Figure 2.3 show an RNN looks like after it's fully unfolded. .

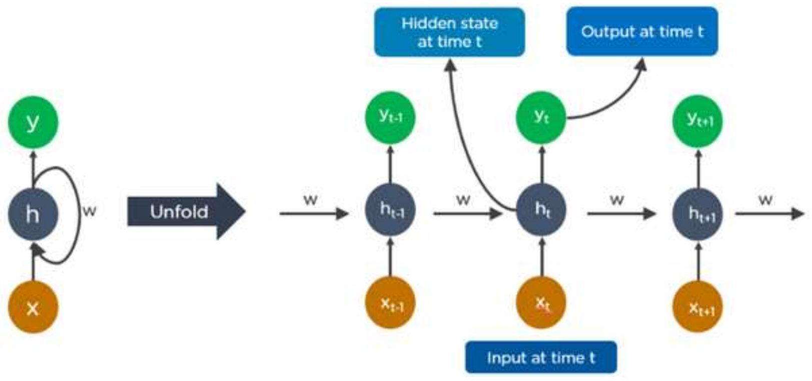

Figure 2.4: Recurrent Neural Networks (RNNs)

At time t-1, the output feeds into the input at time t. The output at time t feeds into the input at time t+1 in the same way. RNNs can handle any length of the input. The computation takes into consideration historical data, and the model size does not grow in proportion to the input size. An example of how Google's auto completing feature works is illustrated in Figure 2.4.

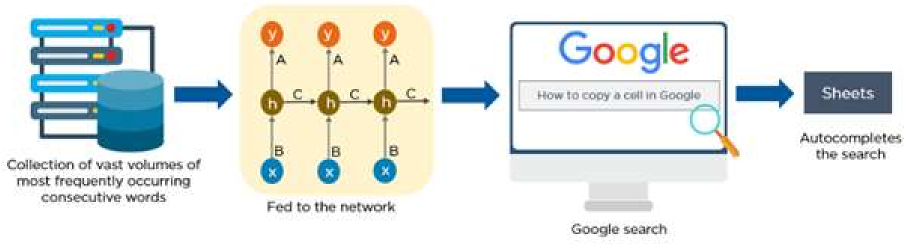
Collection of vast volumes of most frequently occurring consecutive words
Fed to the network
Google
How to copy a cell in Google
Google search
Sheets
Autocompletes the search

Figure 2.5: Recurrent Neural Networks (RNNs) for Google

2.2.4 Restricted Boltzmann Machines (RBMs)

Restricted Boltzmann Machines (RBMs) 12 RBMs are randomized neural networks developed by Geoffrey Hinton that can learn from a probability distribution across a collection of inputs. For dimensionality reduction, classification, regression, collaborative filtering, feature learning, and topic modeling, this deep learning algorithm is utilized. RBMs are the fundamental components of DBNs. RBMs are divided into two layers: visible and hidden units.

Every visible unit is linked to every hidden unit. RBMs have no output nodes and have a bias unit that is coupled to all of the visible and hidden units. RBMs have two phases:

forward pass and backward pass. RBMs accept the inputs and translate them into a set of numbers that encodes the inputs in the forward pass. RBMs combine every input with individual weight and one overall bias.

The algorithm passes the output to the hidden layer. In the backward pass, RBMs take that set of numbers and translate them to form the reconstructed inputs. RBMs combine each activation with individual weight and overall bias and pass the output to the visible layer for reconstruction. At the visible layer, the RBM compares the reconstruction with the original input to analyze the quality of the result. Figure 2.5 illustrates how RBMs function works.

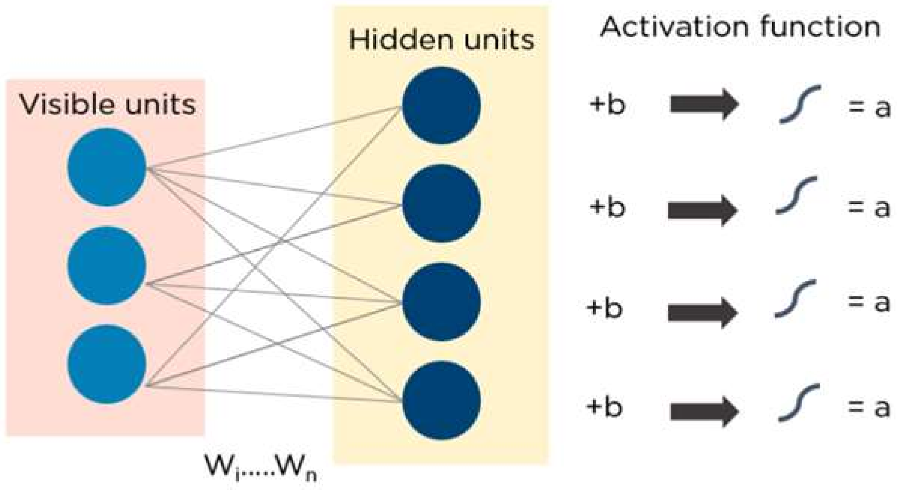

Figure 2.6: Restricted Boltzmann Machines (RBMs)

2.2.5 Autoencoders

Autoencoders are a kind of feed forward neural network where the input and output are both the same. In the 1980s, Geoffrey Hinton invented autoencoders to overcome unsupervised learning difficulties. They're neural networks that have been trained to repeat data from the input layer to the output layer.

Autoencoders are utilized in a variety of applications, including drug discovery, popularity prediction, and image processing. The encoder, the code, and the decoder are the three essential components of an autoencoder. Autoencoders are designed to take in information and turn it into a different form. Then they try to recreate the original input as closely as possible. When a digit's image isn't clear, it's sent into an autoencoder neural network. Autoencoders encode the image first, then compress the data into a smaller form. Finally, the image is decoded by the autoencoder, which produces the reconstructed image..

Autoencoders are used to reduce the dimension of data, as well as to solve problems like novelty detection and anomaly detection.

The first layer in an autoencoder is produced as an encoding layer and then transposed as a decoder. Then, using the unsupervised method, teach it to duplicate the input. Fix the weights of that layer after training. Then go to the next layer until all of the deep net's layers have been pre-trained. Then go back to the original issue (Classification/Regression) that we want to solve with deep learning and optimize it using stochastic gradient descent, starting with the weights learned during pre-training. Autoencoder network consists of two parts. Figure 2.6 shows how autoencoders work.

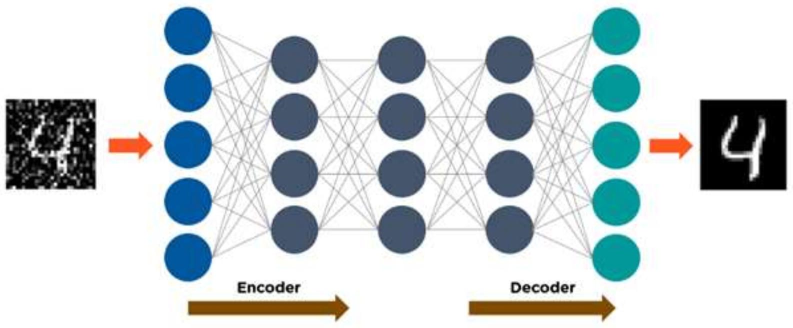

Figure 2.7: Autoencoders

The input is translated to a latent space representation by the encoder, which can be denoted in (1): $h = f(x)$ (1) The input is reconstructed from the latent space representation by the decoder, which can be denoted in (2): $r = g(h)$ (2) In essence, autoencoders can be described in (3). r is the decoded output which will be similar to input x: $g(f(x)) = r$ (3)

CHAPTER 3
Data and Code Implementation

3.1 Architecture of the system

The architecture of this image classification model is a well-thought-out sequence of layers, each contributing uniquely to the model's ability to interpret and classify grayscale clothing images.

1. **Input Layer:**
    - **Functionality:** Represents a 28x28 grid of pixels for a single grayscale clothing image.
2. **Flatten Layer:**
    - **Functionality:** Transforms the 2D image data into a 1D array of 784 values (28x28 pixels), facilitating the transition from spatial information to a format suitable for neural network processing.
3. **Dense Layers (128 neurons, ReLU activation):**
    - **Functionality:** Internal layers responsible for extracting intricate features and patterns from the flattened image data. The ReLU activation function introduces non-linearity to the model, enhancing its ability to capture complex relationships within the data.
4. **Dropout Layer (20%):**
    - **Functionality:** Introduces a regularization technique by randomly dropping 20% of connections during training. This helps prevent overfitting, ensuring the model generalizes well to unseen data.
5. **Output Layer (10 neurons, softmax activation):**
    - **Functionality:** Generates a probability distribution across the 10 clothing classes, providing the final classification predictions for the input image.

Flow of Data:

1. **Image Input:**
    - **Functionality:** A 28x28 grayscale image is fed into the input layer.
2. **Flattening:**

    - **Functionality:** The image is flattened into a 784-element vector, preparing it for processing through subsequent layers.
3. **Processing through Dense Layers:**
    - **Functionality:** The flattened vector traverses the dense layers, where neurons activate based on learned patterns. This process is fundamental for feature extraction and understanding intricate details within the image.
4. **Dropout:**
    - **Functionality:** During training, 20% of connections are randomly dropped, preventing the model from becoming too dependent on specific connections and enhancing its robustness.
5. **Output:**
    - **Functionality:** The final dense layer outputs 10 probabilities, each corresponding to a clothing class. The class with the highest probability is considered the model's prediction.

Additional Points:

- **Training Process:**
    - **Functionality:** The model learns by iteratively adjusting weights and biases based on feedback from labeled training data.
- **Evaluation:**
    - **Functionality:** The model's performance is assessed using a separate test set to determine its accuracy in classifying previously unseen images.
- **Visualizations:**
    - **Functionality:** Although not directly part of the core model functionality, the code includes visualizations to display sample images, predicted labels, and model confidence scores, aiding in understanding and assessing model performance.

Creating a Visual Design:

- **Tools:**
    - Utilize a diagramming tool or software such as Draw.io, Lucidchart, or PowerPoint for creating a visual representation.
- **Components:**
    - Visually represent the input layer, flatten layer, dense layers, dropout layer, and output layer as distinct blocks.
- **Connections:**

    - Use arrows to depict the flow of data between layers.
- **Labels:**
    - Clearly label each component and connection to enhance clarity.
- **Additional Information:**
    - Optionally include boxes for data loading, model compilation, training, and evaluation steps to provide a more comprehensive overview.

3.2 Coding Insights: Unveiling the Model

The following code encapsulates the functionalities discussed above, bringing the model to life. Each line is a testament to the intricacies of image classification, capturing the essence of the input layer's reception to the output layer's decisive predictions. This code serves as a bridge between the theoretical understanding and the practical implementation, providing a tangible representation of the model's architecture. Let's embark on this coding journey and witness the power of deep learning in action.

```
import gzip
import numpy as np
from keras.utils import to_categorical
from keras import layers, models


def load_data(filepath, num_samples):
    with gzip.open(filepath, 'rb') as f:
        data = np.frombuffer(f.read(), dtype=np.uint8, offset=16)
    data = data.reshape((num_samples, 28, 28, 1)).astype(np.float32) / 255.0
    return data


def load_labels(filepath, num_samples):
    with gzip.open(filepath, 'rb') as f:
        labels = np.frombuffer(f.read(), dtype=np.uint8, offset=8)
    return to_categorical(labels, num_classes=10)


# File paths
train_images_path = 'train-images-idx3-ubyte.gz'
train_labels_path = 'train-labels-idx1-ubyte.gz'
test_images_path = 't10k-images-idx3-ubyte.gz'
test_labels_path = 't10k-labels-idx1-ubyte.gz'import tensorflow as tf
mnist = tf.keras.datasets.mnist
```

```
(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.Sequential([
tf.keras.layers.Flatten(input_shape=(28, 28)),
tf.keras.layers.Dense(128, activation='relu'),
tf.keras.layers.Dropout(0.2),
tf.keras.layers.Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
            loss='sparse_categorical_crossentropy',
            metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
            'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']plt.figure()

plt.imshow(train_images[0])
plt.colorbar()
plt.grid(False)
plt.show()
plt.figure(figsize=(10,10))
for i in range(25):
        plt.subplot(5,5,i+1)
        plt.xticks([])
        plt.yticks([])
        plt.grid(False)
        plt.imshow(train_images[i], cmap=plt.cm.binary)
        plt.xlabel(class_names[train_labels[i]])
        plt.show()


model.save(‘model.h5’)
```

3.2.1 Output of the Code Segment

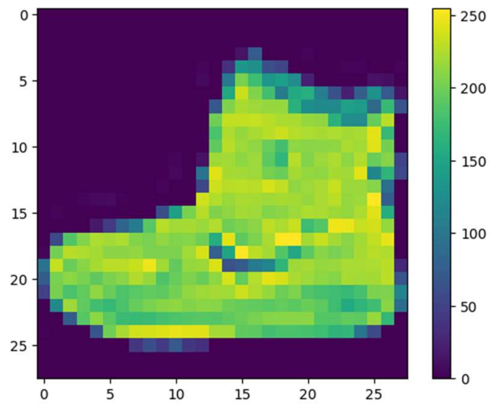

Figure 3.1: The image of a shoe represented using matplotlib

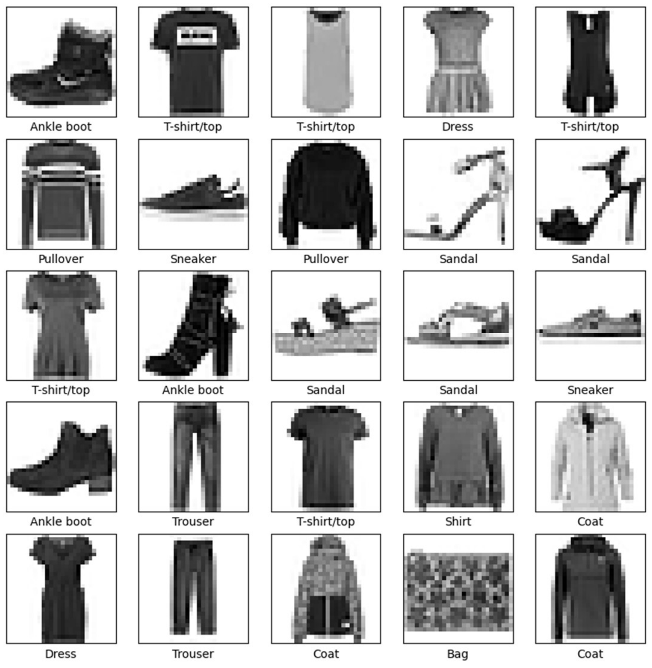

Figure 3.2: The first 25 images subplot

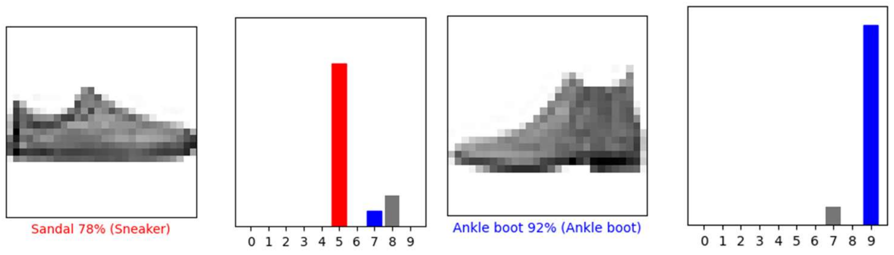

Figure 3.3: Graphical representation of test images data set (red represents incorrect and blue correct prediction of the model)

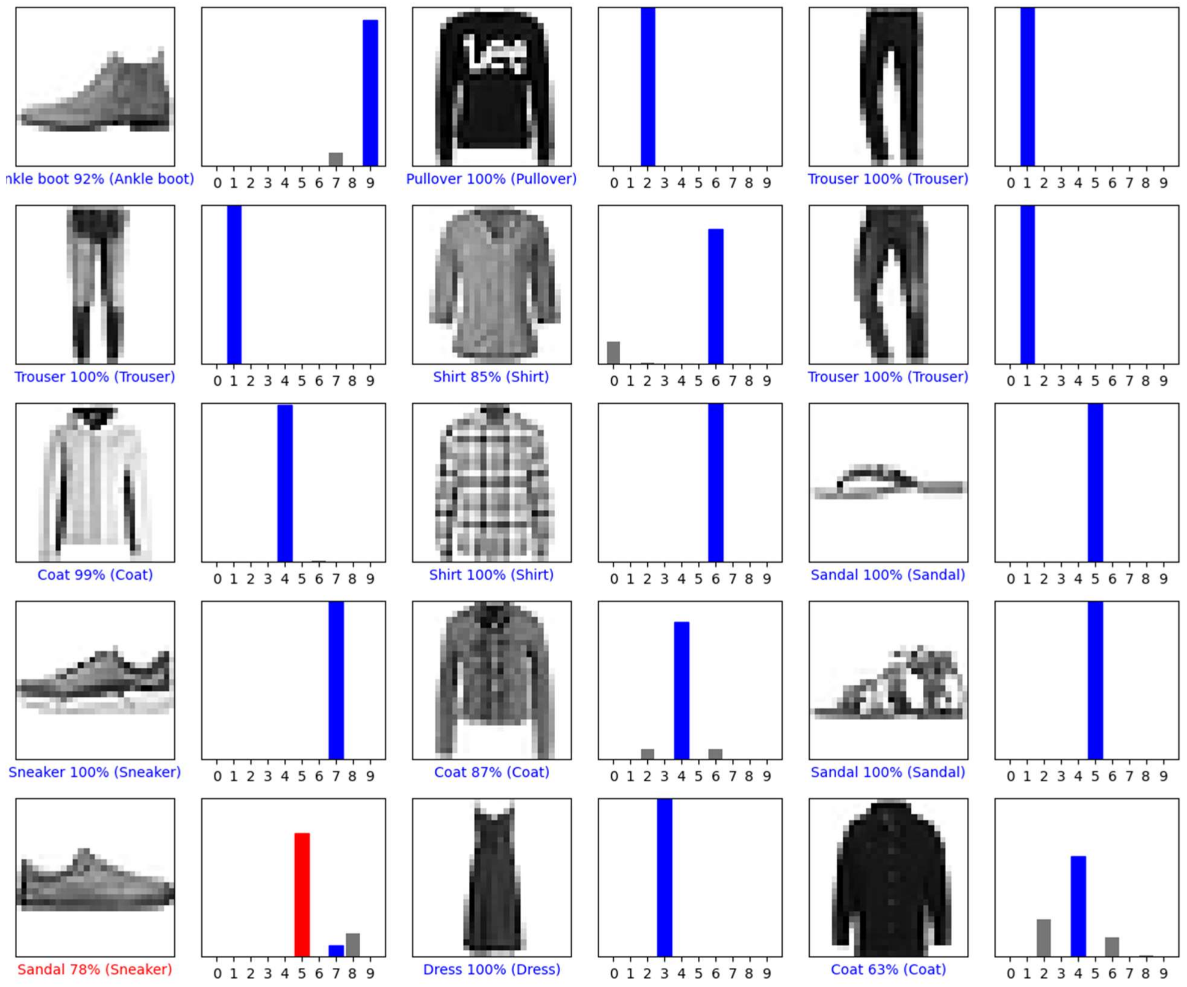

Figure 3.3: Graphical representation of first 25test images data set (red represents incorrect and blue correct prediction of the model)

3.3 Code Discussion and Parameters Selection

1. **import gzip**:
    - **Purpose:** Gzip is a compression and decompression library in Python. In this code, it is used to read data from gzip-compressed files. The **gzip.open** function is employed to open and read binary data from the specified file paths.
2. **import numpy as np**:
    - **Purpose:** NumPy is a powerful numerical computing library in Python. In this code, it is used to perform numerical operations on arrays. The alias **np** is commonly used for brevity. NumPy is employed for processing and reshaping data, converting raw byte data into a suitable format.

3. **from keras.utils import to_categorical**:
    - **Purpose:** Keras is a high-level neural networks API running on top of TensorFlow. The **to_categorical** function from Keras is used to convert integer class labels into one-hot encoded vectors. This is a common preprocessing step when dealing with categorical data, ensuring compatibility with neural network models.
4. **from keras import layers, models**:
    - **Purpose:** Keras provides a convenient and user-friendly interface for building neural networks. The **layers** module contains various types of layers used in neural network architectures, such as dense layers and dropout layers. The **models** module includes the **Sequential** class, which allows the creation of a linear stack of layers.
5. **import tensorflow as tf**:
    - **Purpose:** TensorFlow is an open-source machine learning library, and it serves as the backend for Keras. The **tf** alias is commonly used. In this code, TensorFlow is used for various tasks, including loading a dataset (**mnist**), defining a neural network model (**Sequential** and layers), compiling the model, and training/evaluating the model.

Model Architecture:

Sequential Model: The **Sequential** class is used to create a linear stack of layers. In this case, layers are added sequentially to the model.

Layers:

1. **Flatten Layer:**
    - **Purpose:** Reshapes the input data into a 1D array.
    - **Input Shape:** (28, 28) — This is the shape of each input image, representing a 28x28 pixel grid.
2. **Dense Layer (Hidden Layer):**
    - **Purpose:** A fully connected layer with 128 neurons and ReLU activation function.
    - **Activation Function:** 'relu' — Rectified Linear Unit (ReLU) introduces non-linearity.
3. **Dropout Layer:**
    - **Purpose:** Introduces dropout regularization to prevent overfitting by randomly setting a fraction (0.2 in this case) of input units to zero during training.
    - **Dropout Rate:** 0.2 — 20% of randomly selected neurons are dropped out during each training iteration.
4. **Dense Layer (Output Layer):**

    - **Purpose:** Another fully connected layer with 10 neurons, representing the output classes (digits 0 through 9).
    - **Activation Function:** 'softmax' — Converts raw scores into probabilities, facilitating multi-class classification.

Model Compilation:

- **Optimizer:** 'adam' — Adam optimization algorithm, an adaptive learning rate optimization algorithm.
- **Loss Function:** 'sparse_categorical_crossentropy' — Common choice for multi-class classification problems where the labels are integers.
- **Metrics:** ['accuracy'] — The metric to be evaluated during training and testing is accuracy.

In summary, the model consists of a flattening layer, a dense hidden layer with ReLU activation and dropout, and a dense output layer with softmax activation. The choice of activation functions, dropout, optimizer, and loss function collectively defines the architecture and training configuration of the neural network for the specific task of image classification.

Fitting the Model

- **Epochs:** The parameter **epochs** in the **model.fit** function specifies the number of times the entire training dataset is presented to the neural network for learning. Each epoch consists of multiple iterations, where the model processes batches of data, computes the loss, and adjusts its parameters (weights and biases) using optimization algorithms like gradient descent.
- **Multiple Epochs:** Training a neural network on a dataset just once might not be sufficient for the model to learn complex patterns and relationships within the data. Repeating the process for multiple epochs allows the model to gradually improve its performance by refining its parameters based on the accumulated knowledge from previous passes through the data.
- **Training Dynamics:** In the early epochs, the model might make significant adjustments as it learns from the data. As training progresses, the improvements become smaller, and the model approaches its optimal performance. The number of epochs is a hyperparameter that needs to be tuned based on the specific problem and dataset.
- **Caution:** While using more epochs can lead to better performance, there is a risk of overfitting if the model becomes too specialized to the training data. Monitoring performance on a separate validation dataset during training helps in identifying the point where further training might not yield better generalization to unseen data.

1. **Model Evaluation:**

- **Purpose:** This line evaluates the trained model's performance on the testing dataset (**x_test** and **y_test**). The evaluation typically includes calculating the loss and any specified metrics (in this case, likely accuracy).

2. **Data Visualization:**
   - **Purpose:** These lines create visualizations of the training data. The first block displays a single image from the training dataset (**train_images[0]**), while the second block creates a 5x5 grid of images with their corresponding labels.

3. **Model Saving:**
   - **Purpose:** This line saves the trained neural network model to a file named 'model.h5'. The '.h5' extension indicates that the model is saved in the Hierarchical Data Format (HDF5), a file format commonly used for storing large amounts of numerical data.

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CHAPTER 4
Model Testing using Manual Images

4.1 Coding Segment for Manual Image Testing

```
import os
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing import image
import numpy as np
from PIL import Image

# Function to preprocess an image for prediction using PIL
def preprocess_image_pil(img_path):
    img = Image.open(img_path).convert('L')  # Convert to grayscale
    img = img.resize((28, 28))  # Resize to match model input size
    img_array = np.expand_dims(np.array(img), axis=0)
    img_array = img_array.astype('float32') / 255.0
    return img_array

# Predict and display results for each manual image
for img_file in manual_image_files:
    img_path = os.path.join(manual_folder_path, img_file)

    # Preprocess the image using PIL
    img_array = preprocess_image_pil(img_path)

    # Make a prediction
    predictions = loaded_model.predict(img_array)

    # Get the predicted class index
    predicted_class_index = np.argmax(predictions[0])
```

```
# Display the manual image and its predicted class
   plt.figure()
   plt.imshow(Image.open(img_path).convert('L'))
   plt.title(f'Predicted Class: {class_names[predicted_class_index]}')
   plt.show()
```

Preprocess_image_pil Function:

1. Image.open(img_path).convert('L'):
    - Opens the image located at img_path using the PIL library's Image.open method.
    - The .convert('L') method converts the image to grayscale ('L' mode). This is important because the model expects grayscale images.
2. img.resize((28, 28)):
    - Resizes the image to a 28x28 pixel size. This step is necessary to match the input size expected by the neural network model.
3. np.expand_dims(np.array(img), axis=0):
    - Converts the PIL Image object to a NumPy array and adds an extra dimension at the beginning. This extra dimension is added to represent the batch size, as neural networks typically expect input data in batches.
4. img_array = img_array.astype('float32') / 255.0:
    - Converts the pixel values of the image array to float32 and normalizes them to a range between 0 and 1. This normalization is essential for ensuring that the input data falls within the same scale as the training data.
5. return img_array:
    - Returns the preprocessed image as a NumPy array suitable for input to the neural network model.

Predict and Display the class of the image

1. **Loop Through Manual Images:**
    - The code iterates through each image file in the **manual_image_files** list, where each file represents a manual image.
2. **img_path = os.path.join(manual_folder_path, img_file):**
    - Constructs the full path to the current manual image.

3. **img_array = preprocess_image_pil(img_path):**
   - Calls the **preprocess_image_pil** function to preprocess the manual image and obtain the corresponding NumPy array.
4. **predictions = loaded_model.predict(img_array):**
   - Uses the pre-trained model (**loaded_model**) to make predictions on the preprocessed image.
5. **predicted_class_index = np.argmax(predictions[0]):**
   - Determines the index of the predicted class by finding the position of the maximum value in the predictions array.
6. **Display the Image and Prediction:**
   - Utilizes Matplotlib to display the original manual image along with the predicted class.

4.2 Sending a Manual Image

The following set of 3 images is being used to test the model; the images were neither utilized in the training set or the testing set.

The first image is of a white shirt, the second image is of a racing flag and the last image is of five people wearing a variety of clothes.

The first image is easily found in the class of the model, but the second one does not belong to any class and thus is placed in the nearest class, the last image represents a homogeneous class of clothes and hence the model deduces the class worn by most people.

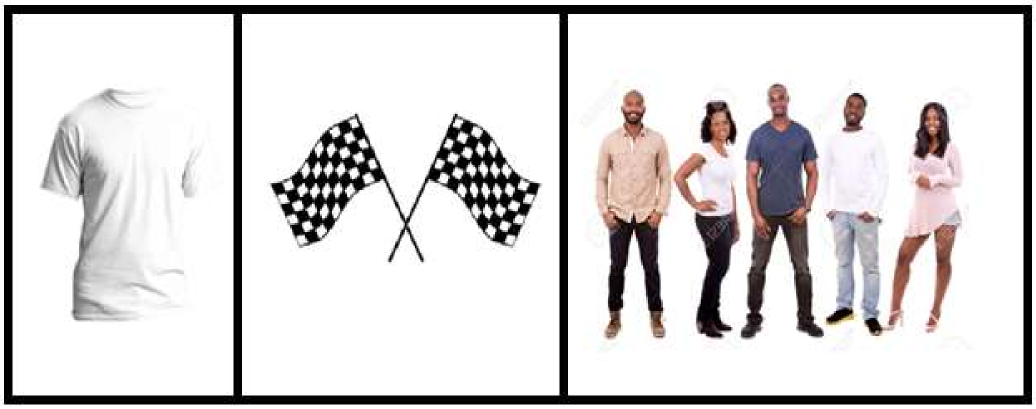

Figure 4.1: The set of 3 images for model testing

The results obtained after testing the model are as follows:

1. The initial image is correctly identified by the model as a shirt.
2. Although the model identifies the second image as a shirt, it is actually a flag, resulting in an incorrect classification.
3. The third image is categorized as a bag due to the cohesive ensemble of clothes it contains.

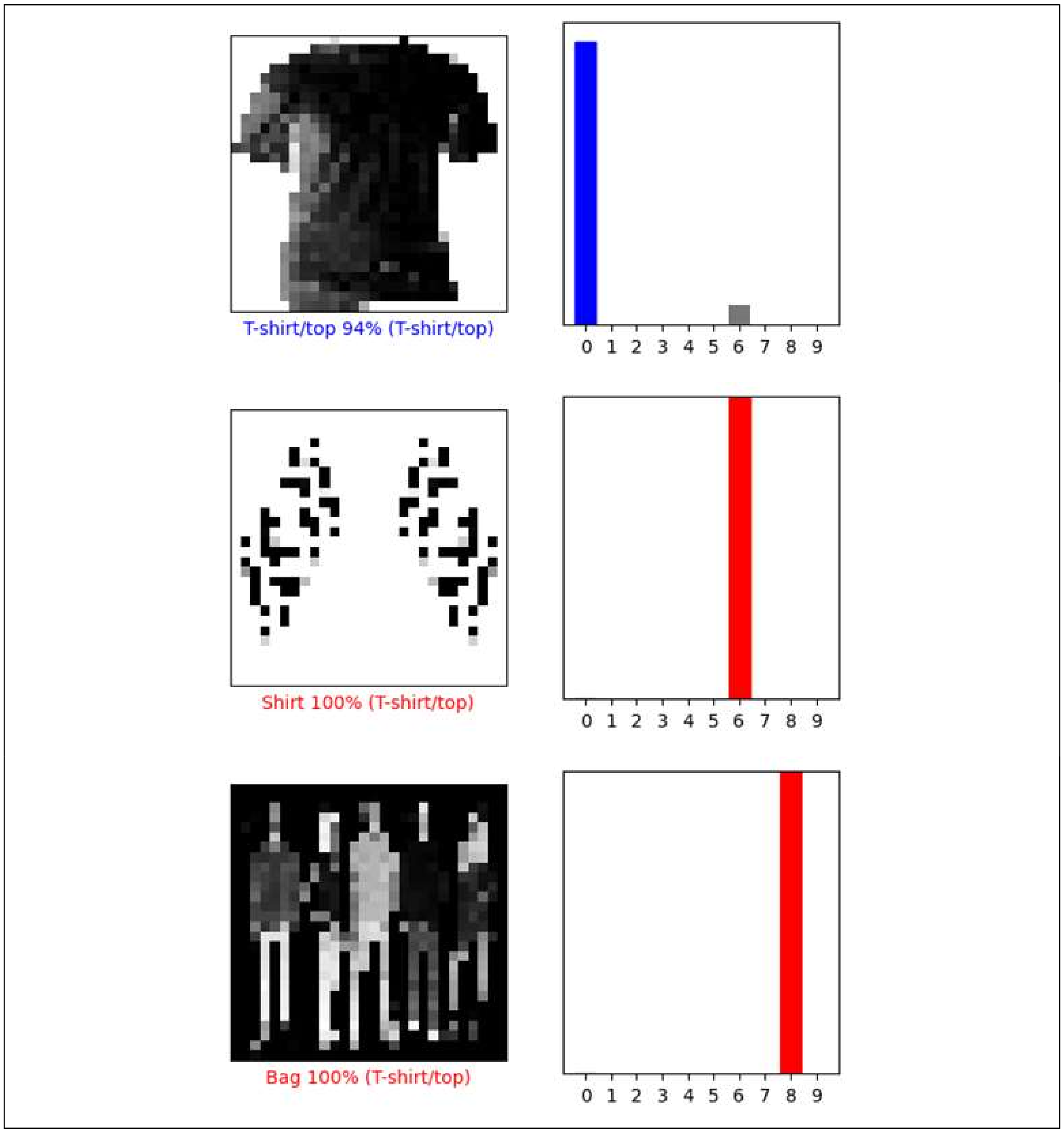

Figure 4.2: Results of the manual images sent on the model

CHAPTER 5

VGG16 in Image Processing

5.1 Overview of the VGG16 Model

A convolutional neural network is also known as a ConvNet, which is a kind of artificial neural network. A convolutional neural network has an input layer, an output layer, and various hidden layers. VGG16 is a type of CNN (Convolutional Neural Network) that is considered to be one of the best computer vision models to date. The creators of this model evaluated the networks and increased the depth using an architecture with very small (3 × 3) convolution filters, which showed a significant improvement on the prior-art configurations. They pushed the depth to 16–19 weight layers making it approx — 138 trainable parameters.
VGG16 is object detection and classification algorithm which is able to classify 1000 images of 1000 different categories with 92.7% accuracy. It is one of the popular algorithms for image classification and is easy to use with transfer learning.

- The 16 in VGG16 refers to 16 layers that have weights. In VGG16 there are thirteen convolutional layers, five Max Pooling layers, and three Dense layers which sum up to 21 layers but it has only sixteen weight layers i.e., learnable parameters layer.
- VGG16 takes input tensor size as 224, 244 with 3 RGB channel
- Most unique thing about VGG16 is that instead of having a large number of hyper-parameters they focused on having convolution layers of 3x3 filter with stride 1 and always used the same padding and maxpool layer of 2x2 filter of stride 2.
- The convolution and max pool layers are consistently arranged throughout the whole architecture
- Conv-1 Layer has 64 number of filters, Conv-2 has 128 filters, Conv-3 has 256 filters, Conv 4 and Conv 5 has 512 filters.
- Three Fully-Connected (FC) layers follow a stack of convolutional layers: the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer.

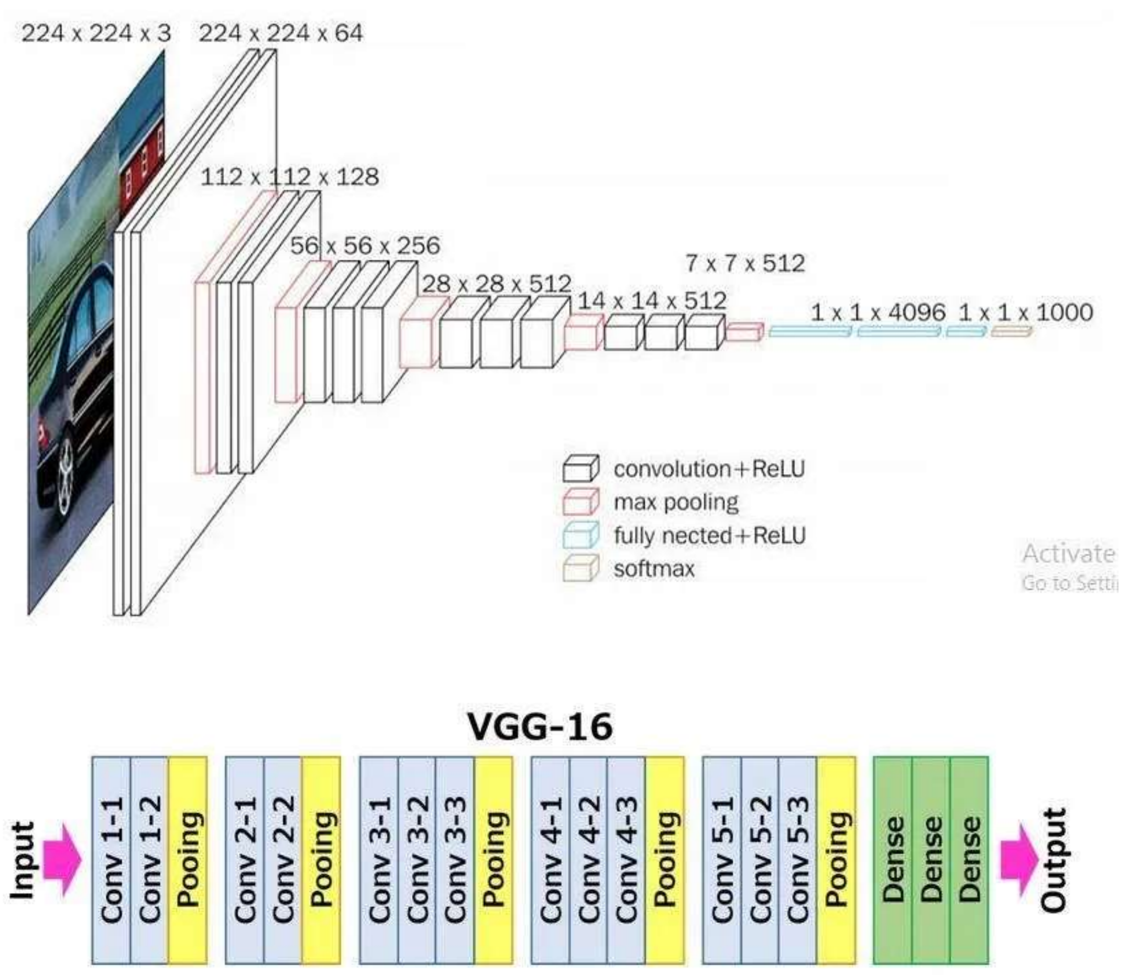

Figure 5.1 : VGG16 Architecture

5.2 Challenges Of VGG 16

- It is very slow to train (the original VGG model was trained on the Nvidia Titan GPU for 2–3 weeks).
- The size of VGG-16 trained imageNet weights is *528* MB. So, it takes quite a lot of disk space and bandwidth that makes it inefficient.

CHAPTER 6
Conclusions and Future Scope

6.1 Conclusion

In conclusion, this report meticulously explores the realm of Python-based deep learning for image classification. From a comprehensive overview of various deep learning algorithms to a practical implementation using the Keras library, the report serves as a holistic guide for researchers, practitioners, and enthusiasts alike.

The emphasis on algorithm selection underscores its crucial role in image classification tasks, with a detailed presentation of the top ten widely used deep learning algorithms. The discussion on dataset considerations, coupled with insights into loading and preprocessing image data using the Keras library, enriches the practicality of the report.

The heart of the report lies in the analysis of results obtained from training the deep learning model. With an accuracy of 87.72%, the efficacy of the chosen algorithm and Python-based implementation is underscored. The code snippets seamlessly integrate theoretical concepts with real-world application, offering a tangible understanding of the implementation process.

To ensure academic rigor, the report provides a comprehensive list of citations and references, serving as a valuable resource for further exploration. Overall, this report is not just a theoretical discourse but a practical guide, bridging the gap between concepts and application in the dynamic landscape of Python-based deep learning for image classification.

6.2 Future Scope

The field of deep learning continues to evolve rapidly, and its future holds numerous exciting possibilities. Some of the potential future directions and areas of growth in deep learning include:

1. **Explainable AI (XAI):**
    - Enhancing the interpretability and transparency of deep learning models is crucial. Researchers are working on developing methods and techniques to make deep learning models more understandable and explainable, especially in critical applications such as healthcare and finance.

2. **Transfer Learning and Pre-trained Models:**
    - Transfer learning, where models trained on one task are adapted for another, will likely become more prevalent. Pre-trained models, especially in natural language processing and computer vision, can be fine-tuned for specific tasks with limited data, making deep learning more accessible.
3. **Reinforcement Learning Advances:**
    - Further advancements in reinforcement learning are expected. This includes more efficient algorithms, improved handling of continuous action spaces, and applications in robotics, finance, and autonomous systems.
4. **Generative Models and Creativity:**
    - Generative models like Generative Adversarial Networks (GANs) are increasingly being used for creative applications, including art generation, style transfer, and content creation. Future developments may involve refining the realism and diversity of generated content.
5. **Edge and Federated Learning:**
    - Deploying deep learning models on edge devices and leveraging federated learning for decentralized training are gaining attention. This allows models to learn from data on the device itself, enhancing privacy and reducing the need for centralized data storage.
6. **AI for Healthcare:**
    - Deep learning is making significant contributions to healthcare, including medical image analysis, drug discovery, and personalized medicine. Future advancements may involve more accurate diagnostic tools, treatment recommendations, and improved patient outcomes.
7. **Automated Machine Learning (AutoML):**
    - The development of tools and frameworks that automate the machine learning pipeline is an ongoing trend. AutoML aims to make machine learning and deep learning more accessible to individuals without extensive expertise, enabling a broader range of applications.
8. **Ethical AI and Bias Mitigation:**
    - Addressing ethical concerns and mitigating biases in deep learning models is a critical focus. Future research will likely emphasize creating models that are fair, unbiased, and considerate of ethical implications, especially in applications like hiring, finance, and criminal justice.

9. **Quantum Machine Learning:**
    - The intersection of quantum computing and machine learning holds promise for solving complex problems that classical computers struggle with. Quantum machine learning algorithms may lead to breakthroughs in optimization and pattern recognition.
10. **Interdisciplinary Collaborations:**
    - Deep learning is increasingly intersecting with other fields such as neuroscience, psychology, and social sciences. Collaborative efforts may yield insights into how biological systems learn and process information, inspiring new directions in deep learning research.

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