Vidyavardhini's
College of Engineering & Technology
Vasai Road (W)

Department of Artificial Intelligence & Data Science

Laboratory Manual
Student Copy

Semester	VIII	Class	B.E
Course Code	CSL801		
Course Name	Advanced Artificial Intelligence Lab		

Vidyavardhini's College of Engineering & Technology

Vision

To be a premier institution of technical education; always aiming at becoming a valuable resource for industry and society.

Mission

- To provide technologically inspiring environment for learning.
- To promote creativity, innovation and professional activities.
- To inculcate ethical and moral values.
- To cater personal, professional and societal needs through quality education.

Department Vision:
To foster proficient artificial intelligence and data science professionals, making remarkable contributions to industry and society.

Department Mission:
- To encourage innovation and creativity with rational thinking for solving the challenges in emerging areas.
- To inculcate standard industrial practices and security norms while dealing with Data.
- To develop sustainable Artificial Intelligence systems for the benefit of various sectors.

Program Specific Outcomes (PSOs):
PSO1: Analyze the current trends in the field of Artificial Intelligence & Data Science and convey their finding by presenting / publishing at a national / international forums.

PSO2: Design and develop Artificial Intelligence & Data Science based solutions and applications for the problems in the different domains catering to industry and society.

Program Outcomes (POs):

Engineering Graduates will be able to:

- **PO1. Engineering knowledge:** Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
- **PO2. Problem analysis:** Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
- **PO3. Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
- **PO4. Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
- **PO5. Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
- **PO6. The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
- **PO7. Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
- **PO8. Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
- **PO9. Individual and teamwork:** Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
- **PO10. Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
- **PO11. Project management and finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
- **PO12. Life-long learning:** Recognize the need for and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

Course Objectives

1	To introduce the concepts of Generative AI
2	To introduce the concepts of GAN
3	To Introduce the concepts of Autoencoders and VAE
4	To introduce the concepts of Ensemble learning and Transfer Learning

Course Outcomes

CO	At the end of course students will be able to:	**Action verbs**	**Bloom's Level**
CSL801.1	Implement a Probabilistic Model for predicting outcomes	Apply	Apply (level 3)
CSL801.2	Apply a GAN on to solve the given problem	Apply	Apply (level 3)
CSL801.3	Apply an appropriate Variational Autoencoder architecture to solve the given problem	Apply	Apply (level 3)
CSL801.4	Apply the concept of Transfer Learning on the given dataset	Apply	Apply (level 3)
CSL801.5	Apply Ensemble Learning techniques to real-world problems	Apply	Apply (level 3)
CSL801.6	Build an Application by making use of Advanced AI concepts	Build	Create (level 6)

Mapping of Experiments with Course Outcomes

List of Experiments	Course Outcomes					
	CSL801.1	CSL801.2	CSL801.3	CSL801.4	CSL801.5	CSL801.6
Prediction of Gold Price Using Hidden Markov Model	3	-	-	-	-	-
Predict the survival on the Titanic using Bayesian Network	3	-	-	-	-	-
Train a Deep Convolution Generative Multi-Layer (DCGAN) Network Model for MNIST dataset.	-	3	-	-	-	-
Train a Variational Autoencoder on Fashion MNIST	-	-	3	-	-	-
Explore the working of any pre-trained model towards outcome generation	-	-	-	3	-	-
Apply XGBOOST for credit fraud detection	-	-	-	-	3	-
Case-study on the implementation AI in Metaverse	-	-	-	-	-	3
Mini-Project	-	-	-	-	-	3

List of Experiments

CSL801: Advanced Artificial Intelligence Lab

Sr. No.	Name of Experiment	DOP	DOC	Marks	Sign
Basic Experiments					
1	Prediction of Gold Price Using Hidden Markov Model				
2	Predict the survival on the Titanic using Bayesian Network				
3	Train a Deep Convolution Generative Multi-Layer (DCGAN) Network Model				
4	for MNIST dataset.				
5	Train a Variational Autoencoder on Fashion MNIST				
6	Explore the working of any pre-trained model towards outcome generation				
Project / Assignment					
7	Case Study on the implementation AI in Metaverse				
8	Course Project: Project Title				
9	Assignment 1: Probabilistic Models				
10	Assignment 2: Generative Adversarial Network				
	Assignment 3: Autoencoders				
	Assignment 4: Transfer Learning				
	Assignment 5: Ensemble Learning				
	Assignment 6: Nascent Technologies in AI				
Formative Assessment					
11	Th - Quiz 1: Generative and Probabilistic Models				
12	Th - Quiz 2: GAN				
13	Th - Quiz 3: VAE				
14	Th - Quiz 4: Transfer Learning				
15	Th - Quiz 5: Ensemble Learning				

16	Th - Quiz 6: Nascent Technologies in AI				
17	Pr - Quiz 1: Implementation of Probabilistic Models				
18	Pr - Quiz 2: Application of GAN				
19	Pr - Quiz 3: Application of VAE				
20	Pr - Quiz 4: Applications of TL concepts				
21	Pr - Quiz 5: Application of Ensemble concepts				
22	Pr - Quiz 6: Build an application				

D.O.P: Date of performance

D.O.C : Date of correction

Experiment No. 1
Prediction of Gold Price Using Hidden Markov Model
Date of Performance:
Date of Submission:

Aim: Prediction of Gold Price Using Hidden Markov Model

Objective: Ablility to implement Hidden Markov Model for prediction

Theory:

The hidden Markov Model (HMM) is a statistical model that is used to describe the probabilistic relationship between a sequence of observations and a sequence of hidden states. It is often used in situations where the underlying system or process that generates the observations is unknown or hidden, hence it has the name "Hidden Markov Model."
It is used to predict future observations or classify sequences, based on the underlying hidden process that generates the data.
An HMM consists of two types of variables: hidden states and observations.

- The hidden states are the underlying variables that generate the observed data, but they are not directly observable.
- The observations are the variables that are measured and observed.

The relationship between the hidden states and the observations is modeled using a probability distribution. The Hidden Markov Model (HMM) is the relationship between the hidden states and the observations using two sets of probabilities: the transition probabilities and the emission probabilities.

- The transition probabilities describe the probability of transitioning from one hidden state to another.
- The emission probabilities describe the probability of observing an output given a hidden state.

Hidden Markov Model Algorithm
The Hidden Markov Model (HMM) algorithm can be implemented using the following steps:
Step 1: Define the state space and observation space
The state space is the set of all possible hidden states, and the observation space is the set of all possible observations.
Step 2: Define the initial state distribution
This is the probability distribution over the initial state.

Step 3: Define the state transition probabilities

These are the probabilities of transitioning from one state to another. This forms the transition matrix, which describes the probability of moving from one state to another.

Step 4: Define the observation likelihoods:

These are the probabilities of generating each observation from each state. This forms the emission matrix, which describes the probability of generating each observation from each state.

Step 5: Train the model

The parameters of the state transition probabilities and the observation likelihoods are estimated using the Baum-Welch algorithm, or the forward-backward algorithm. This is done by iteratively updating the parameters until convergence.

Step 6: Decode the most likely sequence of hidden states

Given the observed data, the Viterbi algorithm is used to compute the most likely sequence of hidden states. This can be used to predict future observations, classify sequences, or detect patterns in sequential data.

Step 7: Evaluate the model

The performance of the HMM can be evaluated using various metrics, such as accuracy, precision, recall, or F1 score.

To summarise, the HMM algorithm involves defining the state space, observation space, and the parameters of the state transition probabilities and observation likelihoods, training the model using the Baum-Welch algorithm or the forward-backward algorithm, decoding the most likely sequence of hidden states using the Viterbi algorithm, and evaluating the performance of the model.

Conclusion:

Comment on the prediction accuracy of the algorithm.

Experiment No. 2
Predict the survival on the Titanic using Bayesian Network
Date of Performance:
Date of Submission:

Aim: Predict the survival on the Titanic using Bayesian Network

Objective: Ablility to implement Bayesian Network for prediction

Theory:

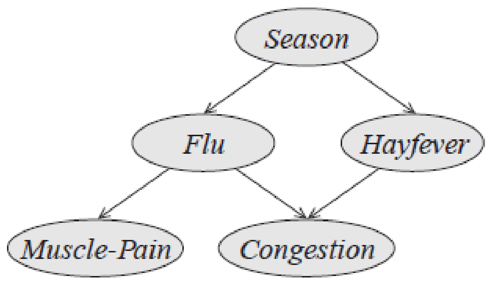
Bayesian Network is directed probability Graphical Model, used to depict cause and effect type of relation between random variables as here arrow is drawn from independent variable to dependent variable.

Using the relationships specified by our Bayesian network, we can obtain a compact, factorized representation of the joint probability distribution by taking advantage of conditional independence.

Bayesian Network is directed acrylic graph where each edge correspond to conditional dependencies and each node correspond to unique random variable.

The Conditional Probability Table associated with each node capture the likelihood of occurrence of that random variable.

Graph Representation

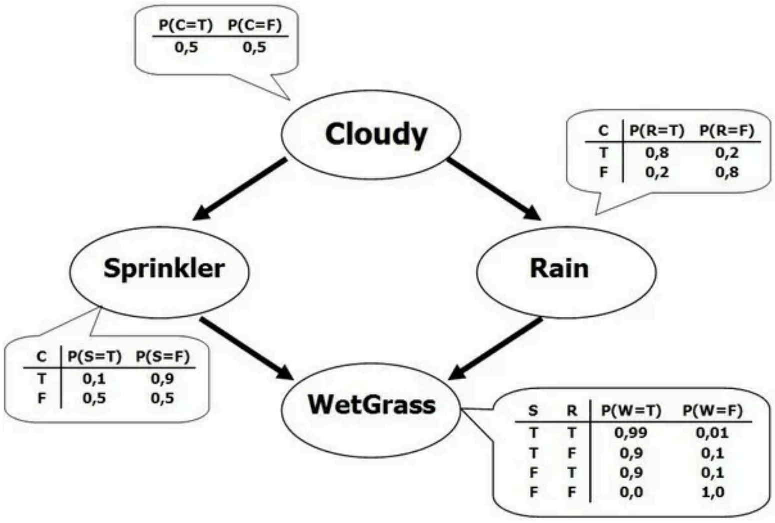


Independencies

$$(F \perp H \mid S)$$
$$(C \perp S \mid F, H)$$
$$(M \perp H, C \mid F)$$
$$(M \perp C \mid F)$$

Factorization

$$P(S, F, H, C, M) = P(S)P(F \mid S)$$
$$P(H \mid S)P(C \mid F, H)P(M \mid F)$$



Applications

1. Medical Diagnosis: BNs are used for diagnosing medical conditions by modeling the relationships between symptoms, test results, and diseases. They can incorporate expert knowledge and update probabilities based on new diagnostic information.

2.Risk Assessment: In fields like finance and insurance, BNs are employed to assess and manage risk. They can model the dependencies between different risk factors, helping decision-makers understand the likelihood and impact of various events.

3. Environmental Modeling: BNs can model complex environmental systems, incorporating variables such as pollution levels, weather conditions, and ecological factors. This is valuable for predicting the impact of changes and making informed decisions in areas like environmental policy.

4. Genetics and Bioinformatics: In genetics, BNs can model the interactions between genes, proteins, and other biological entities. This aids in understanding genetic pathways, predicting the effects of mutations, and analyzing complex biological systems.

5. Manufacturing and Quality Control: BNs are employed in manufacturing to model the relationships between various factors affecting product quality. They can help optimize processes, reduce defects, and improve overall quality control.

6. Fraud Detection: In finance and cybersecurity, BNs can be used for fraud detection. By modeling the relationships between various transactional and behavioral variables, BNs can identify suspicious patterns and activities.

Conclusion:

Comment on the network and the accuracy.

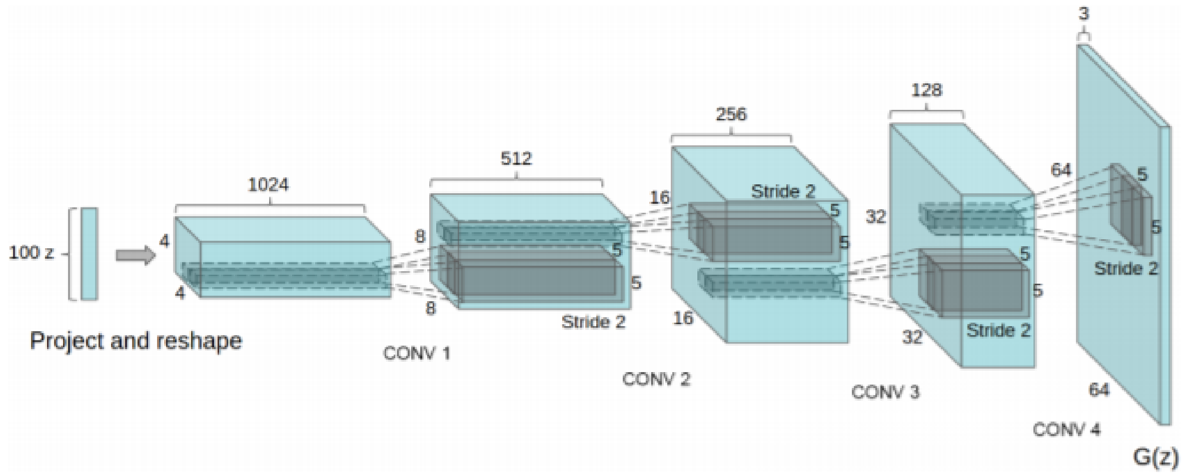
Experiment No. 3
Train a Deep Convolution Generative Multi-Layer (DCGAN) Network Model for MNIST dataset
Date of Performance:
Date of Submission:

Aim: Train a Deep Convolution Generative Multi-Layer (DCGAN) Network Model for MNIST dataset

Objective: Ability to implement Deep Convolution Generative Multi-Layer (DCGAN) Network Model.

Theory:

DCGAN uses convolutional and convolutional-transpose layers in the generator and discriminator, respectively. It was proposed by Radford et. al. in the paper Unsupervised Representation Learning With Deep Convolutional Generative Adversarial Networks. Here the discriminator consists of strided convolution layers, batch normalization layers, and LeakyRelu as activation function. It takes a 3x64x64 input image. The generator consists of convolutional-transpose layers, batch normalization layers, and ReLU activations. The output will be a 3x64x64 RGB image.



Conclusion:

Calculate and comment on the accuracy and structure of the network.

Experiment No. 4
Train a Variational Autoencoder on Fashion MNIST
Date of Performance:
Date of Submission:

Aim: Train a Variational Autoencoder on Fashion MNIST

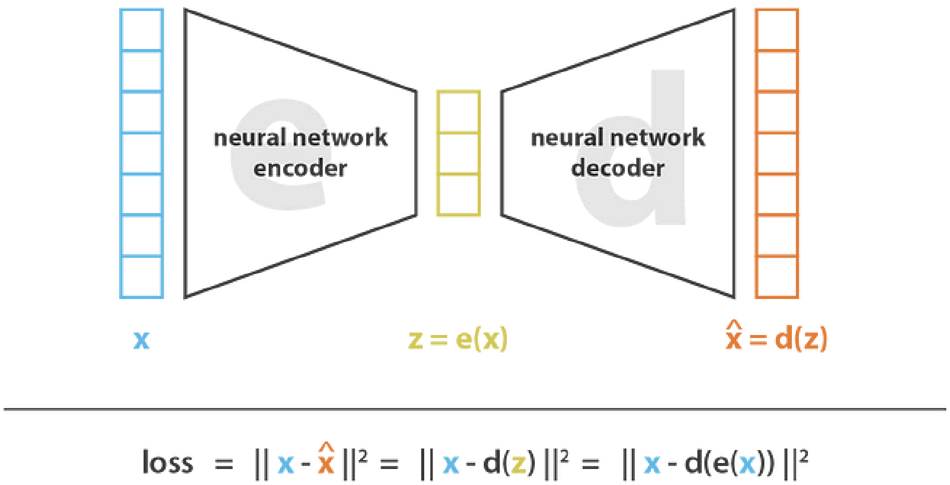
Objective: Ability to implement Variational Autoencoder.

Theory:

Autoencoders:

The general idea of autoencoders is pretty simple and consists in setting an encoder and a decoder as neural networks and to learn the best encoding-decoding scheme using an iterative optimisation process. So, at each iteration we feed the autoencoder architecture (the encoder followed by the decoder) with some data, we compare the encoded-decoded output with the initial data and backpropagate the error through the architecture to update the weights of the networks.

Thus, intuitively, the overall autoencoder architecture (encoder+decoder) creates a bottleneck for data that ensures only the main structured part of the information can go through and be reconstructed. Looking at our general framework, the family E of considered encoders is defined by the encoder network architecture, the family D of considered decoders is defined by the decoder network architecture and the search of encoder and decoder that minimise the reconstruction error is done by gradient descent over the parameters of these networks.



Variational Autoencoders:

A variational autoencoder can be defined as being an autoencoder whose training is regularised to avoid overfitting and ensure that the latent space has good properties that enable generative process.

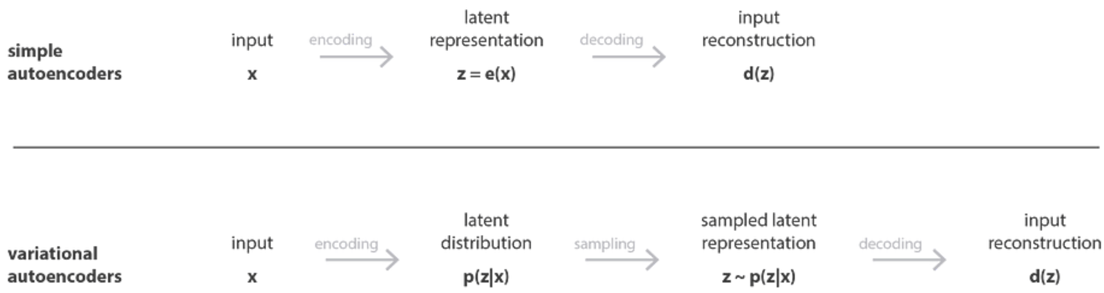
Just as a standard autoencoder, a variational autoencoder is an architecture composed of both an encoder and a decoder and that is trained to minimise the reconstruction error between the encoded-decoded data and the initial data. However, in order to introduce some regularisation of the latent space, we proceed to a slight modification of the encoding-decoding process: instead of encoding an input as a single point, we encode it as a distribution over the latent space. The model is then trained as follows:

first, the input is encoded as distribution over the latent space

second, a point from the latent space is sampled from that distribution

third, the sampled point is decoded and the reconstruction error can be computed

finally, the reconstruction error is backpropagated through the network



Conclusion:

Calculate and comment on the accuracy and structure of the network.

Experiment No. 5
Explore the working of any pre-trained model towards outcome generation
Date of Performance:
Date of Submission:

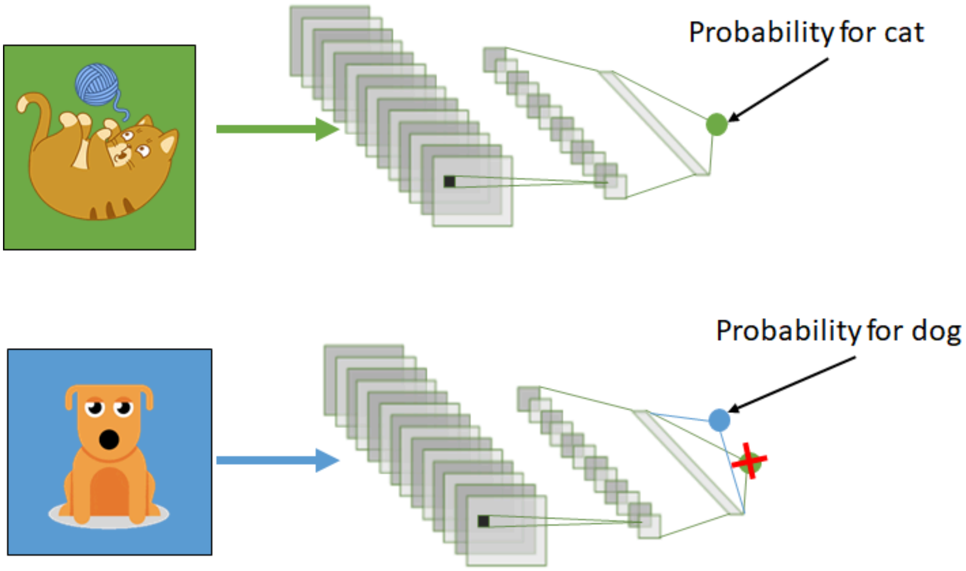
Aim: Explore the working of any pre-trained model towards outcome generation.

Objective: Ability to make use of the pretrained models for a different purpose using the concepts of transfer learning.

Theory:

The reuse of a pre-trained model on a new problem is known as transfer learning in machine learning. A machine uses the knowledge learned from a prior assignment to increase prediction about a new task in transfer learning. You could, for example, use the information gained during training to distinguish beverages when training a classifier to predict whether an image contains cuisine.

The knowledge of an already trained machine learning model is transferred to a different but closely linked problem throughout transfer learning. For example, if you trained a simple classifier to predict whether an image contains a backpack, you could use the model's training knowledge to identify other objects such as sunglasses.



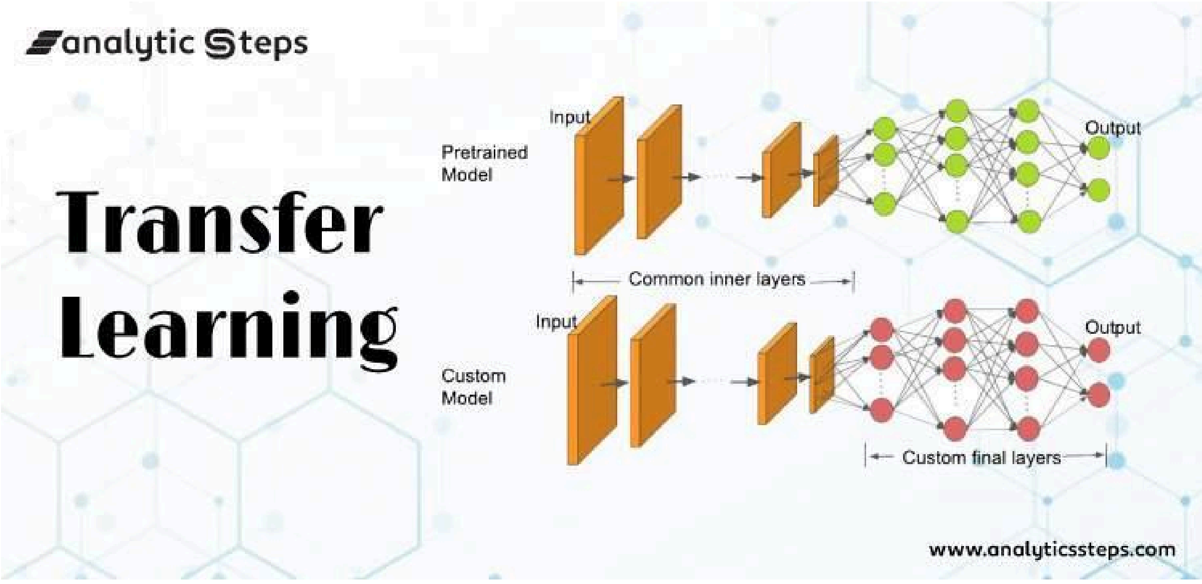
With transfer learning, we basically try to use what we've learned in one task to better understand the concepts in another. weights are being automatically being shifted to a network performing "task A" from a network that performed new "task B."

Because of the massive amount of CPU power required, transfer learning is typically applied in computer vision and natural language processing tasks like sentiment analysis.

How Transfer Learning Works?

In computer vision, neural networks typically aim to detect edges in the first layer, forms in the middle layer, and task-specific features in the latter layers.

The early and central layers are employed in transfer learning, and the latter layers are only retrained. It makes use of the labelled data from the task it was trained on.



Let's return to the example of a model that has been intended to identify a backpack in an image and will now be used to detect sunglasses. Because the model has trained to recognise objects in the earlier levels, we will simply retrain the subsequent layers to understand what distinguishes sunglasses from other objects.

Conclusion:

Comment on the accuracy transfer compared to general prediction/generation.

Experiment No. 6
Apply XGBOOST for credit fraud detection
Date of Performance:
Date of Submission:

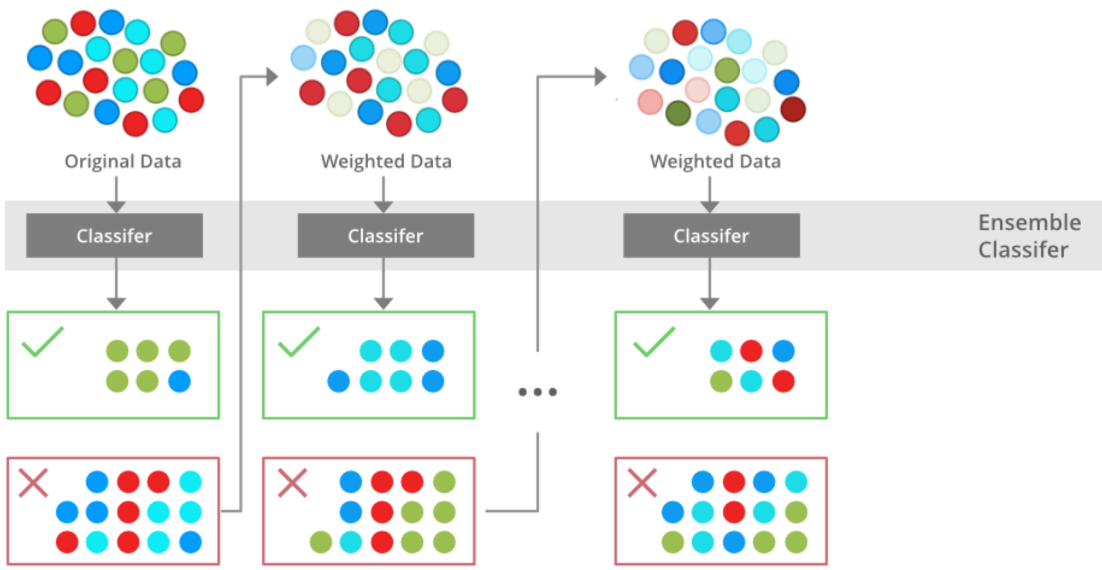
Aim: Apply XGBOOST for credit fraud detection.

Objective: Ability to implement ensemble learning algorithms.

Theory:

Boosting:

Boosting is an ensemble modelling, technique that attempts to build a strong classifier from the number of weak classifiers. It is done by building a model by using weak models in series. Firstly, a model is built from the training data. Then the second model is built which tries to correct the errors present in the first model. This procedure is continued and models are added until either the complete training data set is predicted correctly or the maximum number of models are added.



XGBoost:

XGBoost is an optimized distributed gradient boosting library designed for efficient and scalable training of machine learning models. It is an ensemble learning method that combines the predictions of multiple weak models to produce a stronger prediction. XGBoost stands for "Extreme Gradient Boosting" and it has become one of the most popular and widely used machine learning algorithms due to its ability to handle large datasets and its ability to achieve state-of-the-art performance in many machine learning tasks such as classification and regression.

One of the key features of XGBoost is its efficient handling of missing values, which allows it to handle real-world data with missing values without requiring significant pre-processing. Additionally, XGBoost has built-in support for parallel processing, making it possible to train models on large datasets in a reasonable amount of time.

Conclusion:

Comment on the architecture and the results.

Experiment No. 7
Case-Study on the implementation AI in Metaverse
Date of Performance:
Date of Submission:

Aim: Case-study on the implementation AI in Metaverse

Objective: Ability to study the use cases for the implementation of AI in the Metaverse.

Theory:

Artificial intelligence, or AI, is a special domain of computer science that focuses on using natural language prompts as inputs for generating human-like actions. AI systems are capable of autonomous action, reasoning and learning according to programmed instructions.

You can learn more about AI's role in the metaverse by identifying the core traits of artificial intelligence which align with the metaverse. AI research focuses on developing machines that can process information and understand natural language.

Machines would process data and take decisions like human beings, and they achieve such functionalities by processing the data generated by people every day.

Another significant highlight of AI points to its ability for faster and more efficient data processing. Artificial intelligence applications in the metaverse would rely on the capabilities of machine learning to use data generated in the metaverse. AI could process data to identify patterns and learn from the patterns to improve their performance.

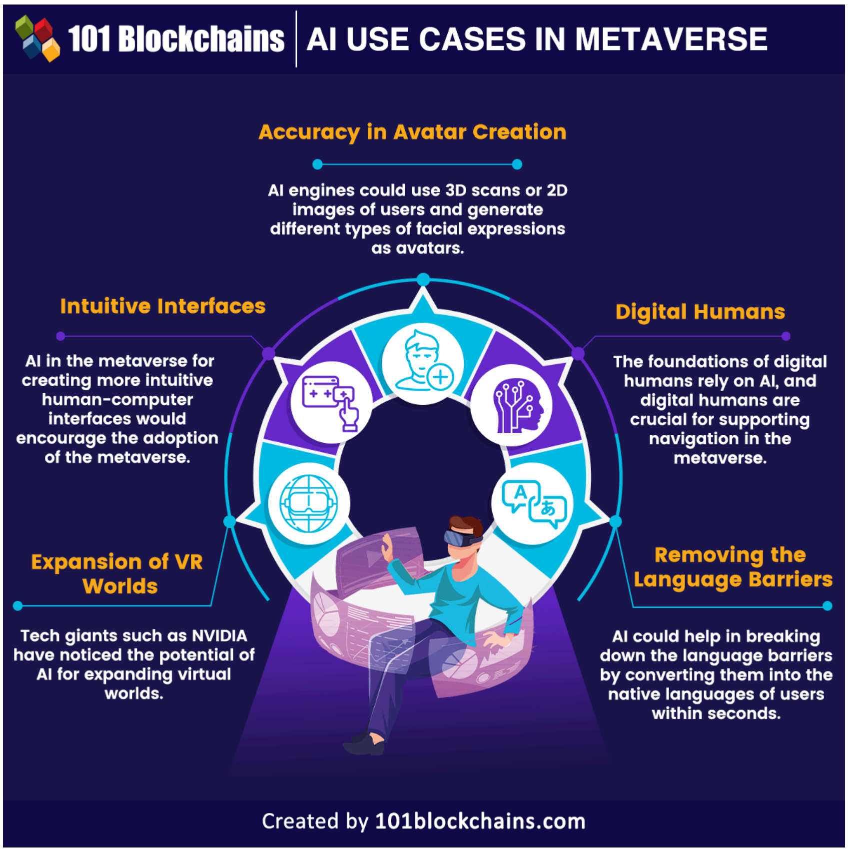
Interestingly, people use simple AI systems in their everyday lives to obtain information. For example, recommendations based on product searches have machine learning working their wonder behind the scenes.

As of now, most of the research on artificial intelligence has been focused on improving the relevance of AI for users. The common theme in research on artificial intelligence revolves around understanding human behaviour and the physical world.

The prospects for an AI-generated metaverse would translate into reality in the future. It is important to note the changing trends in computing, focused on contextual rather than static experiences. The devices around us are gradually adapting and becoming better at understanding and anticipating our needs because of AI.

What are the Use Cases of AI in the Metaverse?

The road to understanding the significance of artificial intelligence would also include a stop at the use cases of AI and metaverse. You can understand how AI and the metaverse work together by reflecting on the applications of artificial intelligence in the metaverse. Virtual worlds of the metaverse could exist without AI. However, the combination of AI and metaverse can unlock new opportunities, as evident in the following use cases.



Conclusion:

Comment on the implementation of AI in the Metaverse.