OVERVIEW: MACHINE LEARNING

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Abstract

Machine learning is a subfield of artificial intelligence that involves the development of algorithms that allow computers to learn from data, without being explicitly programmed. It involves the use of statistical models and algorithms to analyze and identify patterns in data, and make predictions or decisions based on that data. Machine learning algorithms are capable of improving their performance as they are exposed to more data, allowing them to automatically adapt and improve over time. Machine learning is widely used in a variety of applications such as image and speech recognition, natural language processing, recommendation systems, and predictive analytics.

"Machine learning is the science (and art) of programming computers so they can learn from data,"

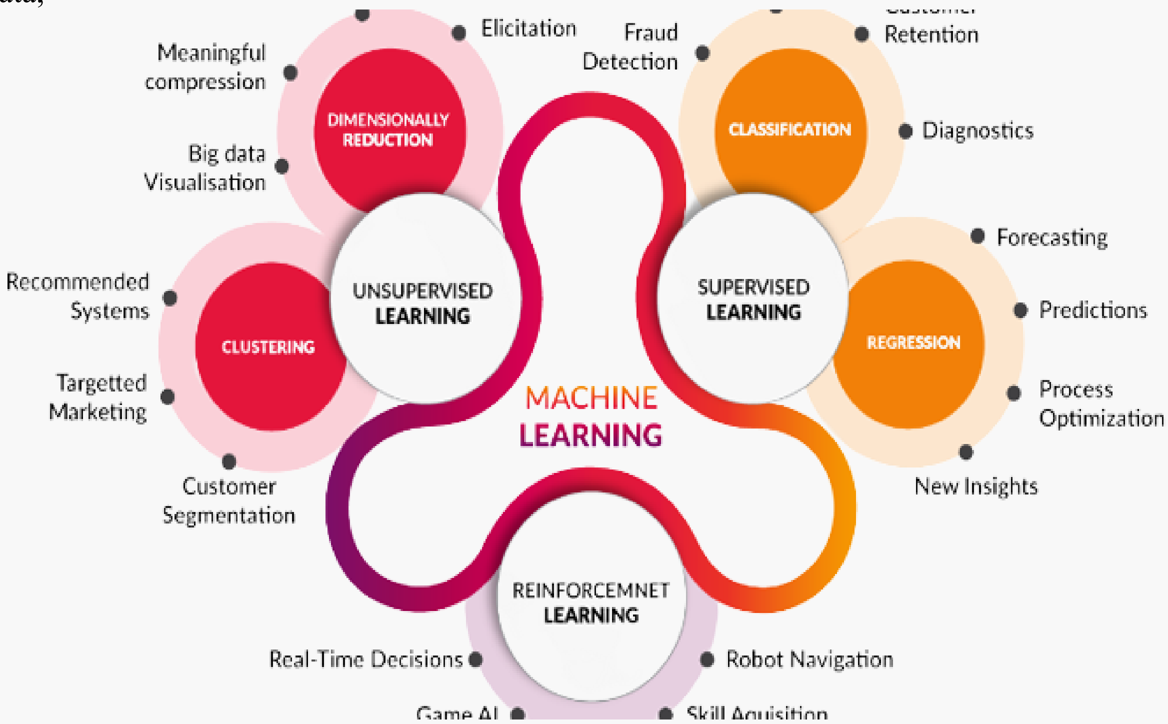

Figure 1: (Machine Learning)

I. MACHINE LEARNING HAS MANY APPLICATIONS ACROSS VARIOUS INDUSTRIES AND DOMAINS, SOME OF WHICH INCLUDE

a. Image and speech recognition
b. b .Natural language processing
c. Predictive maintenance
d. Fraud detection
e. Customer segmentation and personalization
f. Stock market prediction
g. Healthcare diagnosis and treatment recommendation
h. Recommender systems
i. Predictive modeling for climate change and weather forecasting
j. Self-driving cars and autonomous vehicles.

These are just a few examples of the many potential applications of machine learning. The specific use cases will vary depending on the data and problem that is being addressed, as well as the goals of the project and the resources available. In general, machine learning is used to automate tasks that would otherwise be performed by humans, to make predictions and recommendations, and to optimize processes and systems.

II. STEPS OF MACHINE LEARNING

a. Problem definition: Define the problem you want to solve and determine the target variable.
b. Data collection: Gather relevant data to solve the problem.
c. Data exploration: Analyze and understand the data, including cleaning and transforming it if necessary.
d. Model selection: Choose the appropriate model based on the problem and data.
e. Model training: Train the model using the data.
f. Model evaluation: Evaluate the model using appropriate metrics to determine its performance.
g. Model deployment: Deploy the model in a production environment, integrating it with other systems if necessary.

The 7 steps of machine learning are a systematic approach to building predictive models. Firstly, the problem needs to be defined and the target variable identified. This is followed by data collection, where relevant data is gathered to solve the problem. After that, data exploration is carried out to analyze and understand the data, including cleaning and transforming it if necessary. The next step is model selection, where an appropriate model is chosen based on the problem and data. The model is then trained using the data. Following training, the model is evaluated using appropriate metrics to determine its performance. Finally, the model is deployed in a production environment and integrated with other systems if necessary. These steps ensure that machine learning models are built in a structured and repeatable manner, which leads to better results and reduces the risk of failure.

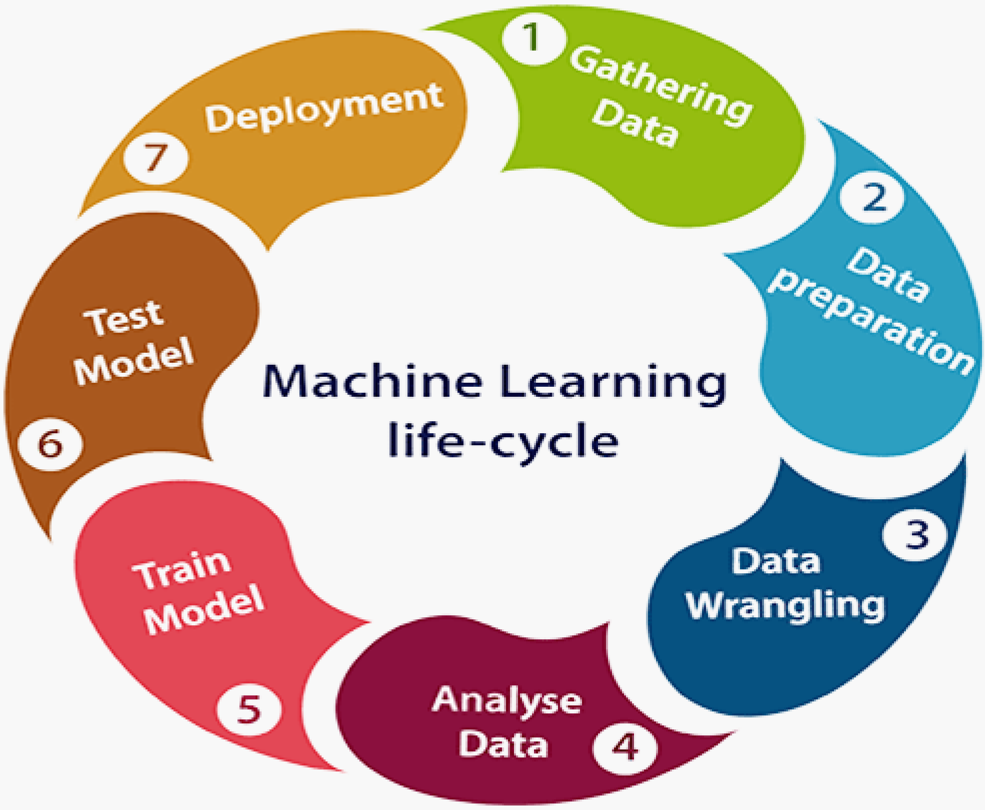

Figure 2: (Steps of Machine Learning)

III. TYPES OF MACHINE LEARNING

a. **Supervised learning:** This type of machine learning involves training a model on labeled data, where the target variable is known. The model makes predictions based on the relationships between the features and target variable.

b. **Unsupervised learning:** This type of machine learning involves training a model on unlabeled data, where the target variable is unknown. The model discovers patterns and relationships in the data without being guided by a specific outcome.

c. **Reinforcement learning:** This type of machine learning involves training a model to make decisions in an environment by receiving rewards or punishments based on its actions. The model learns over time to maximize its rewards.

d. **Semi-Supervised learning:** This type of machine learning combines both supervised and unsupervised learning. It involves training a model on a combination of labeled and unlabeled data, where the model can leverage the relationships learned from the unlabeled data to make better predictions on the labeled data.

e. **Transfer learning:** This type of machine learning involves using a pre-trained model as a starting point and fine-tuning it for a new task, rather than training a model from scratch. This can save time and resources and improve model performance.

A. Supervised Machine Learning

Supervised machine learning is a type of machine learning where the model is trained on labeled data, where the target variable is known. The goal of supervised learning is to build a model that can make predictions about the target variable based on the relationships between the features and the target variable.

In supervised learning, the model is presented with input data (features) and corresponding output data (labels). The model is trained to learn the relationships between the input data and output data. Once the model is trained, it can be used to make predictions on new, unseen data by applying the relationships it learned during training.

Supervised learning is used in a variety of applications, such as image classification, sentiment analysis, and fraud detection. The choice of model used for supervised learning will depend on the specific problem being solved and the characteristics of the data. Common models used in supervised learning include linear regression, decision trees, and support vector machines.

Supervised learning is a powerful tool for making predictions by learning relationships between features and target variables in labeled data.

A.1 Usage of Supervised Machine Learning

Image Classification: Supervised machine learning can be used to classify images into different categories, such as animals, objects, or scenes.

Sentiment Analysis: Supervised machine learning can be used to analyze the sentiment of text data, such as product reviews or social media posts, to determine if they are positive, negative, or neutral.

Fraud Detection: Supervised machine learning can be used to detect fraudulent transactions by learning patterns in the data and flagging transactions that deviate from those patterns.

Predictive Maintenance: Supervised machine learning can be used to predict when equipment will fail, allowing maintenance to be performed before a failure occurs.

Customer Segmentation: Supervised machine learning can be used to segment customers into different groups based on their purchasing behavior, allowing for targeted marketing campaigns.

Sales Forecasting: Supervised machine learning can be used to forecast future sales based on historical sales data and other relevant features.

Recommendation Systems: Supervised machine learning can be used to recommend products or content to users based on their past behavior.

Health care: Supervised machine learning can be used to predict patient outcomes, diagnose diseases, and personalize treatment plans.

A.2 Types of Supervised Machine Learning

a. **Regression:** This type of supervised learning is used for predicting a continuous target variable, such as the price of a stock or the temperature tomorrow. For example, a linear regression model could be used to predict the price of a house based on its size, location, and other features.

b. **Classification:** This type of supervised learning is used for predicting a categorical target variable, such as whether a customer will buy a product or not. For example, a logistic regression model could be used to classify whether an email is spam or not.

c. **Logistic regression:** This type of supervised learning is used for binary classification problems, where the target variable can take on only two possible values. For example, a logistic regression model could be used to predict whether a patient has a disease or not.

d. **Decision trees:** This type of supervised learning builds a tree-like model that uses a series of decisions based on the features to predict the target variable. For example, a decision tree model could be used to predict which type of loan a customer is likely to choose.

e. **Random forest:** This type of supervised learning is an ensemble of decision trees, where multiple trees are trained and combined to make predictions. For example, a random forest model could be used to predict whether a customer will churn or not.

f. **Support vector machines (SVM):** This type of supervised learning uses a boundary called a hyperplane to separate the data into classes. For example, an SVM model could be used to classify images of handwritten digits.

g. **Naive bayes:** This type of supervised learning uses Bayes' theorem to make predictions based on the likelihood of a target variable given the features. For example, a Naive Bayes model could be used to predict the sentiment of a movie review as positive or negative.

h. **Neural networks:** This type of supervised learning uses artificial neural networks to model complex relationships between the features and target variable. For example, a neural network model could be used to predict the prices of stocks.

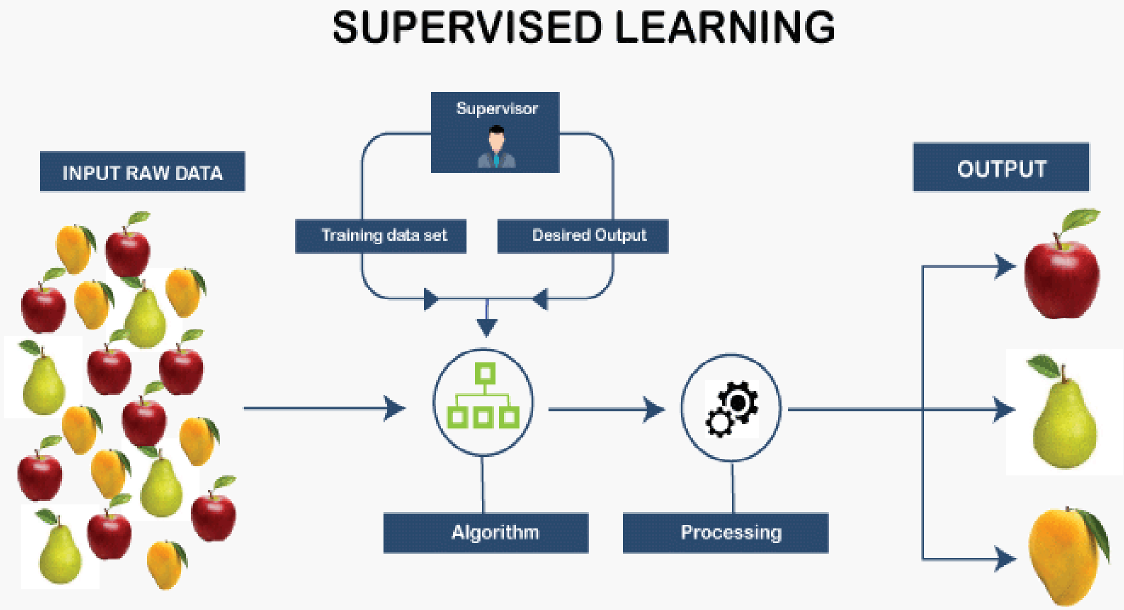

Figure 4: (Supervised Machine Learning)

B. Unsupervised Machine Learning

Unsupervised learning algorithms can be divided into two main categories: clustering and dimensionality reduction. Clustering algorithms aim to group similar data points together, while dimensionality reduction algorithms aim to reduce the number of features in the data while preserving its structure.

Examples of unsupervised learning algorithms include k-means clustering, hierarchical clustering, and principal component analysis. These algorithms are useful in a variety of applications, such as customer segmentation, anomaly detection, and data visualization.

In unsupervised learning, there is no right or wrong answer, and the quality of the model is often determined by subjective measures such as the interpretability of the results and their usefulness in a particular domain. However, unsupervised learning can be more challenging than supervised learning because the model is not guided by a specific outcome, and it is more difficult to evaluate the performance of the model.

Despite these challenges, unsupervised learning is an important tool in the machine learning arsenal and has many real-world applications. It provides valuable insights into the underlying structure of the data and can lead to the discovery of new patterns and relationships.

B.1 Usage of Unsupervised Machine Learning

Customer Segmentation: Grouping customers into segments based on their behavior, preferences, and purchasing habits.

Anomaly Detection: Detecting unusual or unexpected behavior in a data set, such as fraud detection or network intrusion.

Data Visualization: Reducing the dimensionality of a data set for easy visualization and interpretation.

Recommender Systems: Recommend products or items to users based on their past behavior and preferences.

Image and Speech Processing: Clustering images or speech segments to identify patterns and relationships.

Natural Language Processing: Grouping words into topics and identifying relationships between words.

Fraud Detection: Identifying unusual patterns or behavior in financial transactions that may indicate fraud.

Text Clustering: Grouping documents into categories based on their content.

Image Compression: Reducing the size of an image while preserving its features and structure.

Gene Expression Analysis: Identifying patterns and relationships in gene expression data for biological research.

B.2 Types of Unsupervised Machine Learning

- **a. Clustering:** This type of unsupervised machine learning is used to group similar data points into clusters. For example, grouping customers into segments based on their purchasing habits.

- **b. Dimensionality reduction:** This type of unsupervised machine learning is used to reduce the number of features in a data set while preserving its structure. For example, reducing the number of variables in a high-dimensional data set for visualization or further analysis.

- **c. Anomaly detection:** This type of unsupervised machine learning is used to identify unusual or unexpected patterns in a data set. For example, detecting fraud in financial transactions.

- **d. Association rule learning:** This type of unsupervised machine learning is used to find relationships between variables in a data set. For example, identifying items that are frequently purchased together in a grocery store.

- **e. Auto encoders:** This type of unsupervised machine learning is used to learn a compact representation of a data set. For example, reducing the size of an image while preserving its features and structure.

f. Generative adversarial networks (GANs): This type of unsupervised machine learning is used to generate new data samples that are similar to a training data set. For example, generating realistic images of faces.

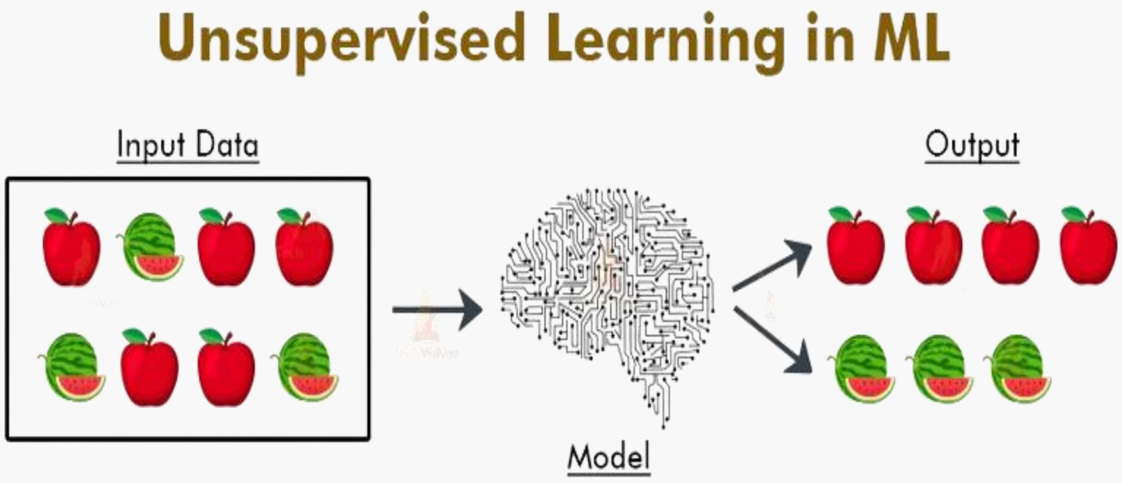

Figure 5: (Unsupervised Machine Learning)

C. Reinforcement Machine Learning

Reinforcement machine learning is a type of artificial intelligence that focuses on training models to make decisions in an environment by receiving rewards or punishments based on their actions. The goal is to learn a policy, which is a mapping from states to actions, that maximizes a reward signal over time.

In reinforcement learning, an agent interacts with an environment by observing the state of the environment, taking an action, and receiving a reward or punishment. The agent's goal is to maximize the total reward it receives over time. The agent learns from trial and error, adjusting its policy based on the rewards and punishments it receives.

Reinforcement learning has applications in various fields such as gaming, robotics, and autonomous systems. For example, it can be used to train a computer to play a game by receiving rewards for good moves and punishments for bad moves. In robotics, reinforcement learning can be used to train robots to perform tasks in an environment by receiving rewards for successful completion and punishments for failure.

Reinforcement learning algorithms can be broadly categorized into two categories: value-based and policy-based. Value-based algorithms learn a function that maps states to values, which represent the expected reward for being in that state. Policy-based algorithms learn a policy directly, without estimating a value function.

Reinforcement learning is an active area of research and continues to evolve, with new algorithms and techniques being developed to solve morecomplex problems.

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C.1 Usage of Reinforcement Machine Learning

Gaming: Reinforcement learning can be used to train AI agents to play games such as chess, poker, and Go.

Robotics: Reinforcement learning can be used to train robots to perform tasks in real-world environments, such as grasping objects or navigation.

Autonomous Systems: Reinforcement learning can be used to develop autonomous systems, such as self-driving cars, that can make decisions in real-world environments.

Finance: Reinforcement learning can be used to develop trading algorithms for financial markets.

Healthcare: Reinforcement learning can be used to optimize treatment plans for patients and improve patient outcomes.

Marketing: Reinforcement learning can be used to optimize advertising and marketing campaigns by learning from the outcomes of past actions.

Supply Chain Management: Reinforcement learning can be used to optimize supply chain operations by making decisions about production, inventory, and transportation.

C.2 Types of Reinforcement Machine Learning

a. **Value-based:** Value-based reinforcement learning algorithms learn a function that maps states to values, which represent the expected reward for being in that state. An example of a value-based reinforcement learning algorithm is Q-Learning, which is used to train AI agents to play games such as chess and Go.

b. **Policy-based:** Policy-based reinforcement learning algorithms learn a policy directly, without estimating a value function. An example of a policy-based reinforcement learning algorithm is REINFORCE, which is used in robotics to train robots to perform tasks such as grasping objects or navigation.

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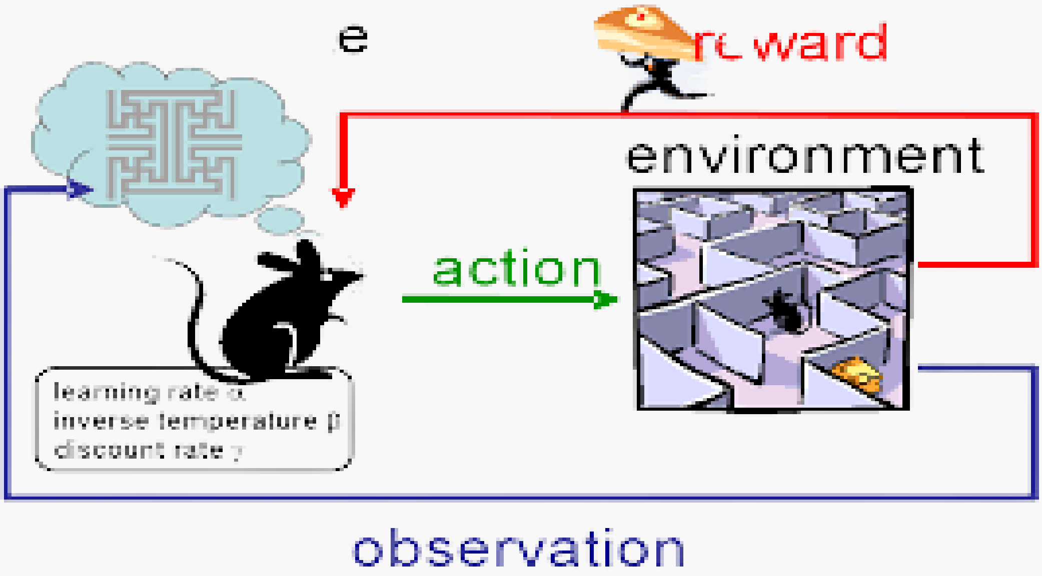

Figure 5: (Reinforcement Machine Learning)

D. Semi-Supervised Machine Learning

Semi-supervised machine learning is a type of machine learning where the algorithm is trained on a mixture of labeled and unlabeled data. In traditional supervised learning, the algorithm is trained on a dataset with labeled examples, where the label is the desired output for a given input. In unsupervised learning, the algorithm is trained on a dataset with no labels, and it must find patterns in the data without any guidance.

Semi-supervised learning aims to combine the strengths of both supervised and unsupervised learning. By using a small amount of labeled data, the algorithm can learn the underlying structure of the data and make predictions for new, unlabeled examples. This can be especially useful in situations where obtaining labeled data is time-consuming, expensive, or difficult.

Semi-supervised learning algorithms can be broadly categorized into two categories: generative and discriminative. Generative algorithms model the joint distribution of the inputs and labels, while discriminative algorithms model the conditional distribution of the labels given the inputs.

Semi-supervised learning is an active area of research and continues to evolve, with new algorithms and techniques being developed to handle increasingly complex datasets and scenarios.

Some real-world examples of semi-supervised learning include natural language processing tasks, such as text classification and named entity recognition, where large amounts of unlabeled text data can be used to improve performance. Additionally, semi-supervised learning can be used in image classification, where the algorithm is trained on a combination of labeled and unlabeled images.

D.1 Usage of Semi-Supervised Machine Learning

Natural Language Processing: Semi-supervised learning is often used in NLP tasks, such as text classification, named entity recognition, and sentiment analysis. In these tasks, large amounts of unlabeled text data can be used to improve the performance of the algorithm.

Image Analysis: Semi-supervised learning can be used in image classification tasks, where the algorithm is trained on a combination of labeled and unlabeled images. This can be useful when labeled data is limited, as the algorithm can still learn the underlying structure of the data.

Healthcare: Semi-supervised learning can be used in healthcare to predict patient outcomes or diagnose diseases. In these scenarios, a small amount of labeled data can be used to make predictions for new, unlabeled patients.

Fraud Detection: Semi-supervised learning can be used to detect fraudulent activity in financial systems. In these systems, labeled data is often limited, but the algorithm can still learn from the vast amounts of unlabeled data to make predictions.

Marketing: Semi-supervised learning can be used in marketing to make predictions about customer behavior. For example, the algorithm can learn from a combination of labeled data about customers who have made a purchase and unlabeled data about customers who have not made a purchase.

D.2 Types of Semi-Supervised Machine Learning:

a. Semi-supervised classification: This involves using both labeled and unlabeled data to classify a target variable.
Example: Image classification with a small labeled dataset and a large unlabeled dataset.

b. Semi-supervised regression: This involves using both labeled and unlabeled data to predict a continuous target variable.
Example: Predicting house prices based on a small labeled dataset and a large dataset of neighborhood features.

c. Self-training: This involves using a small labeled dataset to train a model and then using the model's predictions on the unlabeled data to generate pseudo-labels, which can then be used to improve the model.
Example: Sentiment analysis using a small labeled dataset and a large unlabeled dataset of customer reviews.

d. Co-Training: This involves training two or more models on different views of the same data and using their predictions to label the unlabeled data and improve the models.
Example: Named entity recognition using two models trained on different views of the same text data.

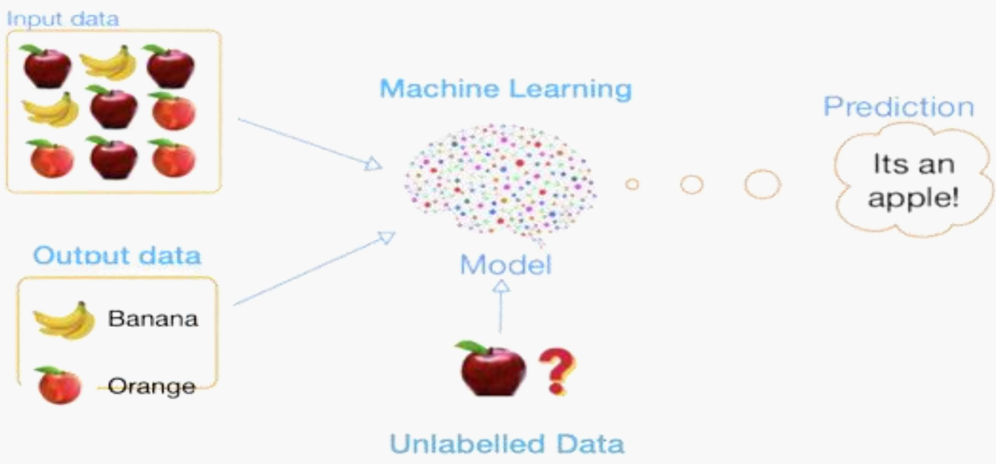

Figure 6: (Semi-Supervised Machine Learning)

E. Transfer Machine Learning

Transfer learning is a machine learning technique where a model trained on one task is fine-tuned on a different but related task. The idea is to transfer knowledge learned on the original task to the new task, making it easier and faster to train. This is particularly useful when the amount of data available for the new task is limited, and the model can leverage the knowledge learned from the previous task to perform well on the new task.

E.1 Usage of Transfer Machine Learning

Computer Vision: Transfer learning is widely used in computer vision tasks such as object detection, image classification, and semantic segmentation.

Natural Language Processing: Transfer learning is used in NLP tasks such as sentiment analysis, text classification, and named entity recognition.

Healthcare: Transfer learning has been applied in the healthcare field to diagnose diseases, predict patient outcomes, and analyze medical images.

Speech recognition: Transfer learning has been used in speech recognition tasks to improve the accuracy of speech-to-text models.

Robotics: Transfer learning has been applied in robotics to improve control systems and perception tasks.

E.2 Types of Transfer Machine Learning

a. **Instance-based transfer learning:** Example: Using a pre-trained image classification model on ImageNet to classify objects in photographs of a specific location, like a zoo.

b. **Feature-based transfer learning:** Example: Using a pre-trained model's intermediate layer activations as features for a new classifier trained to solve a related but different problem, like recognizing a new set of objects.

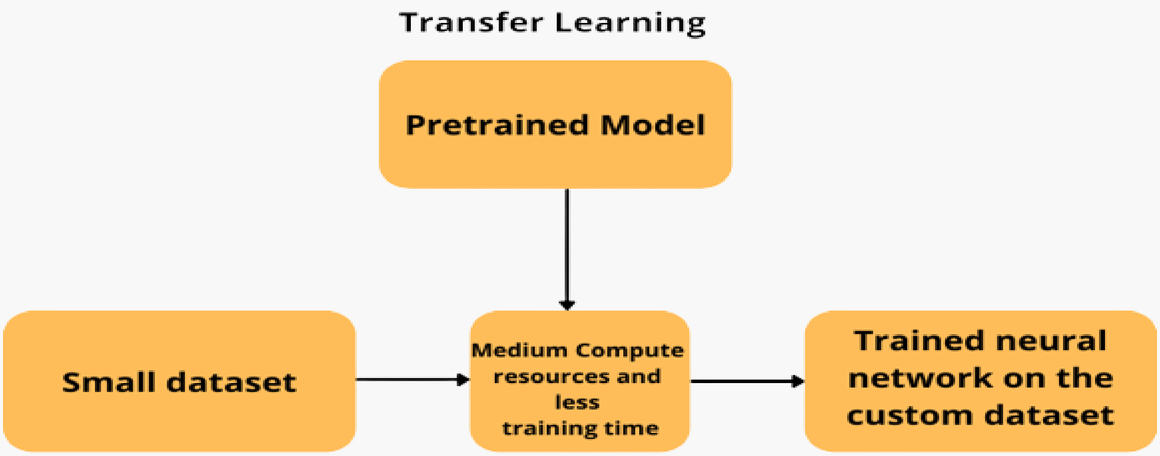

Figure 7: (Transfer Machine Learning)

REFERENCES

[1] L. Yan, C. Rong, and G. Zhao, "Strengthen cloud computing security with federal identity management using hierarchical identity-based cryptography," Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 5931 LNCS, pp. 167–177, 2009.
[2] B. Hamlen, K., Kantarcioglu, M., Khan, L. and Thuraisingham, "Security Issues for Cloud Computing," Proc. - 9th Int. Conf. Comput. Intell. Secur. CIS 2013, pp. 150–162, 2012.
[3] M. a. AlZain, E. Pardede, B. Soh, and J. a. Thom, "Cloud computing security: From single to multi-clouds," Proc. Annu. Hawaii Int. Conf. Syst. Sci., pp. 5490–5499, 2011.
[4] C. Wang, Q. Wang, K. Ren, and W. Lou, "Privacy-preserving public auditing for data storage security in cloud computing," Proc. - IEEE INFOCOM, 2010.
[5] T. Swathi, K. Srikanth, and S. R. Reddy, "Virtualization in Cloud Computing," Int. J. Comput. Sci. Mob. Comput., vol. 35, no. 5, pp. 540–546, 2014.
[6] C. Modi, D. Patel, B. Borisaniya, A. Patel, and M. Rajarajan, "A survey on security issues and solutions at different layers of Cloud computing," J. Supercomput., vol. 63, no. 2, pp. 561–592, 2013.
[7] S. Subashini and V. Kavitha, "A survey on security issues in service delivery models of cloud computing," J. Netw. Comput. Appl., vol. 34, no. 1, pp. 1–11, 2011.
[8] S. K. Abd, R. T. Salih, and F. Hashim, "Cloud Computing Security Risks with Authorization

Access for Secure Multi-Tenancy Based on AAAS Protocol," IEEE Reg. 10 Conf. TENCON, pp. 1– 5, 2015.
[9] H. Aljahdali, A. Albatli, P. Garraghan, P. Townend, L. Lau, and J. Xu, "Multi-tenancy in cloud computing," Proc. - IEEE 8th Int. Symp. Serv. Oriented Syst. Eng. SOSE 2014, pp. 344–351, 2014.
[10] N. Kshetri, "Privacy and security issues in cloud computing: The role of institutions and institutional evolution," Telecomm. Policy, vol. 37, no. 4–5, pp. 372–386, 2013.
[11] K. Hashizume, D. Rosado, E. Fernández-Medina, and E. Fernandez, "An analysis of security issues for cloud computing," J. Internet Serv. Appl., vol. 4, no. 5, pp. 1–13, 2013.
[12] F. Sabahi, "Virtualization-level security in cloud computing," in 2011 IEEE 3rd International Conference on Communication Software and Networks, 2011, pp. 250–254.
[13] S. Carlin, "Cloud Computing Security," Artif. Intell., vol. 3, no. March, pp. 14–16, 2011.
[14] R. Buyya, R. Buyya, C. S. Yeo, C. S. Yeo, S. Venugopal, S.Venugopal,J.Broberg,J.Broberg,I.Brandic,andI.Brandic,"Cloudcomputing and emerging IT platforms:Vision,hype, andreality fordeliveringcomputingasthe5thutility,"Futur.Gener.Comput.Syst.,vol.25,no.6,p.17,2009.
[15] J. Kabbedijk, C.-P. Bezemer, S. Jansen, and A. Zaidman, "Defining multi-tenancy: A systematic mapping study on the academic and the industrial perspective," J. Syst. Softw., vol. 100, pp. 139–148, 2015.
[16] J. Espadas, A. Molina, G. Jim??nez, M. Molina, R. Ram??rez, and D. Concha, "A tenant- based resource allocation model for scaling Software-as-a-Service applications over cloud computing infrastructures," Futur. Gener. Comput. Syst., vol. 29, no. 1, pp. 273– 286, 2013.
[17] H. Aljahdali, P. Townend, and J. Xu, "Enhancing multi-tenancy security in the cloud IaaS model over public deployment," Proc. - 2013 IEEE 7th Int. Symp. Serv. Syst. Eng. SOSE 2013, pp. 385–390, 2013.
[18] R. Wu, G.-J. Ahn, H. Hu, and M. Singhal, "Information flow control in cloud computing," 2010 6th Int. Conf. Collab. Comput. Networking, Appl. Work., pp. 1–7, 2010.
[19] M. Ali, S. U. Khan, and A. V. Vasilakos, "Security in cloud computing: Opportunities and challenges," Inf. Sci. (Ny)., vol. 305, pp. 357–383, 2015.
[20] F. Zhang and H. Chen, "Security-Preserving Live Migration of Virtual Machines in the Cloud," J. Netw. Syst. Manag., pp. 562–587, 2012.
[21] W. A. Jansen, "Cloud hooks: Security and privacy issues in cloud computing," Proc. Annu. Hawaii Int. Conf. Syst. Sci., no. iv, p. 42, 2011.
[22] K. Sunil Rao and P. Santhi Thilagam, "Heuristics based server consolidation with residual resource defragmentation in cloud data centers," Futur. Gener. Comput. Syst., vol. 50, pp. 87–98, 2015.
[23] J. Wei, X. Zhang, G. Ammons, V. Bala, and P. Ning, "Managing security of virtual machine images in a cloud environment," Proc. 2009 ACM Work. Cloud Comput. Secur. - CCSW '09, no. Vm, p. 91, 2009.
[24] M. Kazim, R. Masood, and M. A. Shibli, "Securing the virtual machine images in Cloud computing," SIN 2013 - Proc. 6th Int. Conf. Secur. Inf. Networks, pp. 425–428, 2013.
[25] R. Schwarzkopf, M. Schmidt, C. Strack, S. Martin, and B. Freisleben, "Increasing virtual machine security in cloud environments," J. Cloud Comput. Adv. Syst. Appl., vol. 1, no. 1, p. 12, 2012.
[26] D. Jeswani, A. Verma, P. Jayachandran, and K. Bhattacharya, "ImageElves: Rapid and reliable system updates in the cloud," Proc. - Int. Conf. Distrib. Comput. Syst., no. i, pp. 390–399, 2013.
[27] K. Fan, D. Mao, Z. Lu, and J. Wu, "OPS: Offline patching scheme for the images management in a secure cloud environment," Proc. - IEEE 10th Int. Conf. Serv. Comput. SCC 2013, pp. 587–594, 2013.
[28] Cloud Security Alliance, "Cloud Controls Matrix Working Group," 2014. [Online]. Available: https://cloudsecurityalliance.org/group/cloud-controls-matrix/.
[29] R. Sandhu, D. Ferraiolo, and R. Kuhn, "The NIST model for role-based access control," Proc. fifth ACM Work. Role-based access Control - RBAC '00, pp. 47–63, 2000.

[30] H. J. Smith, S. J. Milberg, and S. J. Burke, “Information Privacy: Measuring Individuals’ Concerns about Organizational Practices,” Manag. Inf. Syst. Q., vol. 20, no. 2, pp. pp. 167–196,1996.
[31] M. Zhou, R. Zhang, W. Xie, W. Qian, and A. Zhou, “Security and privacy in cloud computing: A survey,” Proc. - 6th Int. Conf. Semant. Knowl. Grid, SKG 2010, pp. 105–112, 2010.
[32] R. Sandhu and S. Jajodia, “Integrity principles and mechanisms in database management systems,” Comput. Secur., vol. 10, no. 5, pp. 413–427, 1991.
[33] SK Tiwari, DS Rajput, S Sharma, SG Neogi, A Mishra,”Cloud Virtual Image Security for Medical Data Processing”,Mathematical Modeling and Soft Computing in Epidemiology, 317-345, 2020.
[34] Tiwari, S.K., Neogi S. G., Shakya H.K., Mishra A.,Devaraju T., “ Design and Implementation of a Virtualization Security Technique for Cloud Computing”, *Computer Integrated Manufacturing Systems*, *28*(12), 114–123,2022.
[35] Tiwari, S.K., Neogi S. G., Mishra A. Securing Virtual Images in Cloud Environment”, *Mathematical Statistician and Engineering Applications*, *71*(4), 7871–7882,2023.
[36] Tiwari, S.K., Neogi, S.G., Mishra, A. (2023). Design and Implementation of Security Enhancement for Trusted Cloud Computing. In: Kumar, A., Mozar, S., Haase, J. (eds) Advances in Cognitive Science and Communications. ICCCE 2022.Cognitive Science and Technology.Springer, Singapore.
[37] Tiwari,S.K. Sao,N., Kushwaha, A.,Book Title “Fundamental of Machine Learning”,lambert Publication,ISBN: 9789391265335, Oct. 2022.