Scientific Journal of Computer Science
futuristech PT. Teknologi Futuristik Indonesia
Date of publication February 9, 2025, date of current version February 9, 2025.
Digital Object Identifier ***10.64539/sjcs.v1i1.2025.18***

Review

Machine Learning 5.0 In-depth Analysis Trends in Classification

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The author(s) received no financial support for the research, authorship, and/or publication of this article.

Abstract: In the era of Technology 5.0 Machine Learning continues to show significant advancements across various sectors. This study aims to examine the latest trends in Machine Learning classification, focusing on four key approaches Explainable Artificial Intelligence, Federated Learning, Transfer Learning, and Generative Adversarial Networks. The methodology involves a comprehensive literature review of research in Asia and experimentation with related datasets. The findings indicate that Explainable Artificial Intelligence enhances transparency and accuracy in data classification, Federated Learning enables decentralized learning while safeguarding data privacy, Transfer Learning improves accuracy with small datasets, and Generative Adversarial Networks aids in data augmentation for better model training. In conclusion, these techniques not only enhance the efficiency and accuracy of classification but also open up new opportunities for innovation in various fields, including healthcare, transportation, and cybersecurity.

Keywords: Machine Learning; Explainable AI; Federated Learning; Transfer Learning; Generative Adversarial Networks

1. Introduction

Machine Learning (ML) is an increasingly popular field that is widely used across various sectors such as education, healthcare, politics, business, and government. This field enables data analysis and prediction based on algorithms for improved decision-making. As a part of Artificial Intelligence (AI), ML can mimic human intelligence in decision-making processes. Based on data suitability, ML is divided into four types (Figure 1): Supervised Learning, Unsupervised Learning, Semi-Supervised Learning, and Reinforcement Learning.

Here, we will briefly discuss the key components of ML. The first one is Supervised ML, which is a learning process that begins with labeled data, where each label provides insight into the classification of the data [1]. The main objective of this learning process is to identify patterns that can be utilized in analytical processes. For instance, if you have a dataset of animal images, each labeled with a description, you can train a ML model to recognize and distinguish different animal species [1]. A case example is when data is labeled with animal types, which may include hundreds of species categories. Since the data already has clear attributes and meanings, users can easily train a model using the available labels. If the labels are continuous values, the approach used is regression; whereas if the labels are from a limited number of categories, the approach is called classification. Regression in supervised learning aims to understand the relationship between variables. One example of its application is weather forecasting, where regression analysis is used to predict weather conditions based on historical patterns and current conditions [1]. The algorithms commonly used in supervised learning include Naïve Bayes and Support Vector Machine [2], Speech Emotion Recognition [3], Decision Support System [4], Classification of patients with major depressive disorder [5]. **Unsupervised ML** refers to a type of data learning that operates without human supervision. In this approach, the system analyzes datasets that are not labeled and seeks to uncover hidden patterns in the data without any human intervention. [6]. This type will perform data clustering based on similar patterns from data features, as implemented by algorithms such as K-Means and GMM. [7], network technology improvements [8], Cyber-Physical Systems [9].**Semi-Supervised Learning** is a technique that utilizes both small and large amounts of data, whether labeled or unlabeled. Labeling a large volume of data manually can be cumbersome during processing; therefore, this technique provides a solution. This approach has two primary methods: self-training and co-training. The self-training and co-training methods both leverage labeled and unlabeled data for classification or regression tasks. In self-training, an initial model is built using a small amount of labeled data, and then unlabeled data is classified through pseudo-labeling. The pseudo-labeled data is combined with the labeled data to create a new, augmented dataset that enhances prediction accuracy. On the other hand, co-training is a more complex method often used for classifying data such as websites. It involves creating separate classification models for different views with a small amount of labeled data, followed by the addition of unlabeled data with pseudo-labeling. This data is then processed to identify correct and incorrect classifications. Ultimately, predictions from the two updated classification models are merged to produce a more optimal final result, such as in remote sensing image classification [10]. **Reinforcement Learning** is a ML technique that trains software to make optimal decisions through a trial-and-error approach. Using a reward and punishment paradigm, RL algorithms learn from feedback to find the best path toward a final outcome. This technique enables algorithms to delay gratification in order to achieve a better overall strategy, even if it involves temporary sacrifices or penalties. RL is highly effective in helping AI systems achieve optimal results in previously uncharted environments, as demonstrated in the case of crypto agents. [11], Management of Diabetes [12], Optimization of Snake-Like [13].

After understanding the four main types of ML, it is important to highlight one of its application areas that has a significant impact, namely classification. [1,14]. Classification is a technique in ML used to group data into categories or numerical values, and it is a part of supervised learning. In classification, data splitting is required, such as training data and testing data [15]. Classification can be found in everyday life in today's technology-driven era, such as email filtering, which predicts whether an email is classified as spam or not [16]. The email undergoes a training phase first, where the model is trained to recognize characteristics of messages containing spam. Afterward, the model is tested, and the output classifies the emails into spam or non-spam categories.

Classification in ML is a predictive process where a model uses classification algorithms to assign the appropriate labels to input data. As an AI model is trained to analyze and classify data within a training dataset, its ability to recognize different types of data, detect patterns, and make accurate predictions improves. After the training process is completed, the model's performance is evaluated using test data. Computer scientist David Wolpert emphasizes the importance of algorithm selection in each case. Selecting the right algorithm is crucial for addressing any problem. The challenge lies in determining how to make this choice. When computational resources are abundant, one can test multiple algorithms and parameter settings. The primary concern then becomes how to accurately estimate and compare the performance of these algorithms. [17].

At the time this paper is written, the world has entered the 5.0 technology era, where technology has become deeply integrated with humans and serves as an inseparable support in everyday life. This era is characterized by the fusion of advanced technologies, such as AI, with human needs to create more personalized and adaptive solutions. In this context, this paper will delve deeper into classification in ML, which has become one of the key aspects in the 5.0 technology era. The discussion will cover the role of classification in data-driven decision-making, the challenges faced, and its potential applications to support innovation across various fields.

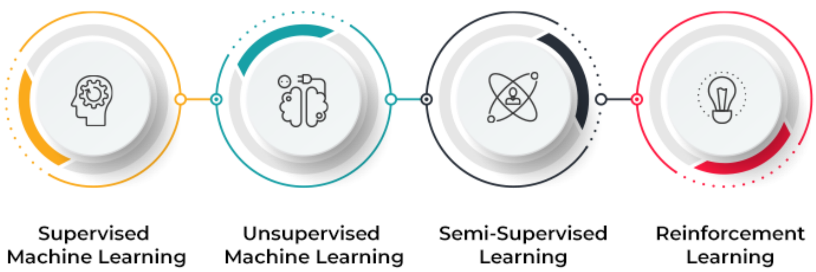

Figure 1. Types of ML.

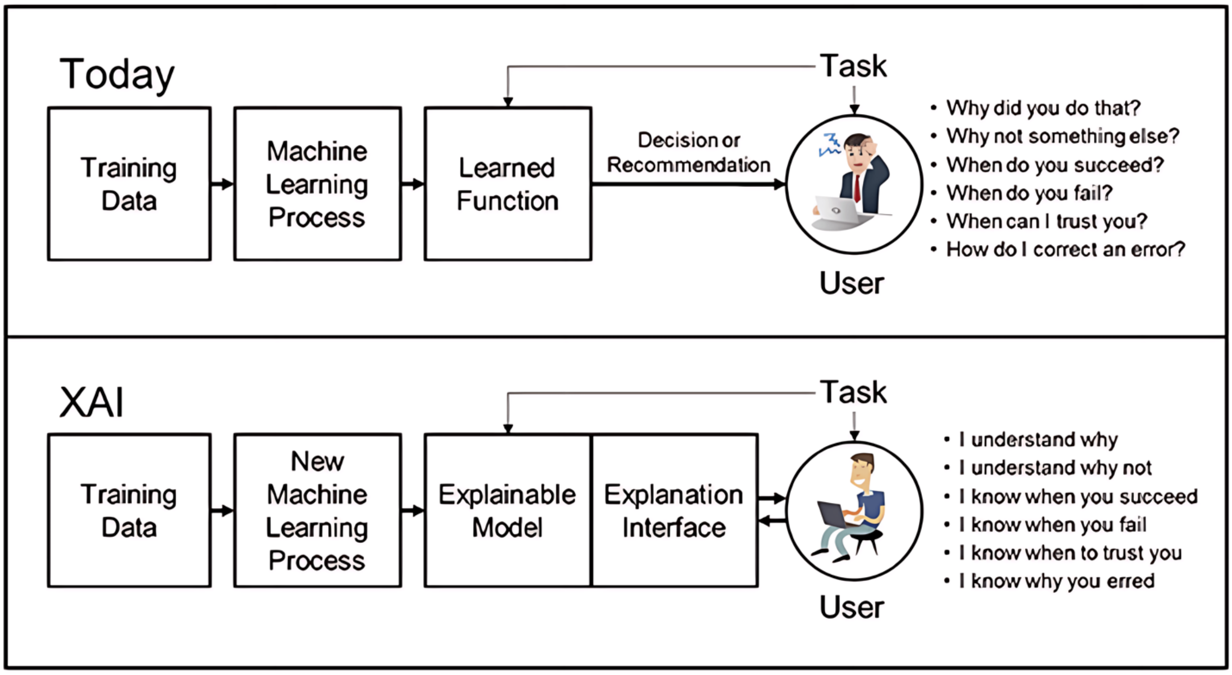

Figure 2. AI Potential VS Explainable AI [18].

2. Latest Trends 5.0 in Classification.

2.1. Explainable AI

XAI holds great potential to enhance the understanding of models in relation to data that evolves over time. [19]. One example of this is the **relevance-based neural freezing** [20] The development aimed at addressing the issue of catastrophic forgetting, which refers to the loss of old knowledge when a model learns new data. Figure 2 will describe XAI vs AI.

XAI has been successfully implemented in research to distinguish between real and synthetic images using the CIFAKE dataset [21], The use of XAI in the ecology sector for biodiversity monitoring [22], The quality of fruits and vegetables in terms of shape, color, and size to avoid losses for the superstore [23], In the agricultural sector, XAI is also applied to analyze pollen, which plays a vital role [24].

2.2. Federated Learning

Federated Learning (FL) is a ML method in which multiple clients (such as mobile devices or organizations) collaborate to train a model under the coordination of a central server (e.g., service providers), while keeping the training data decentralized [25]. FL applies the principle of focused and minimal data collection, thereby reducing privacy risks and systemic costs often associated with traditional centralized ML approaches. Recently, this field has garnered significant attention, both in terms of research and its applications [25]. Figure 3: An Overview of the FL Cycle.

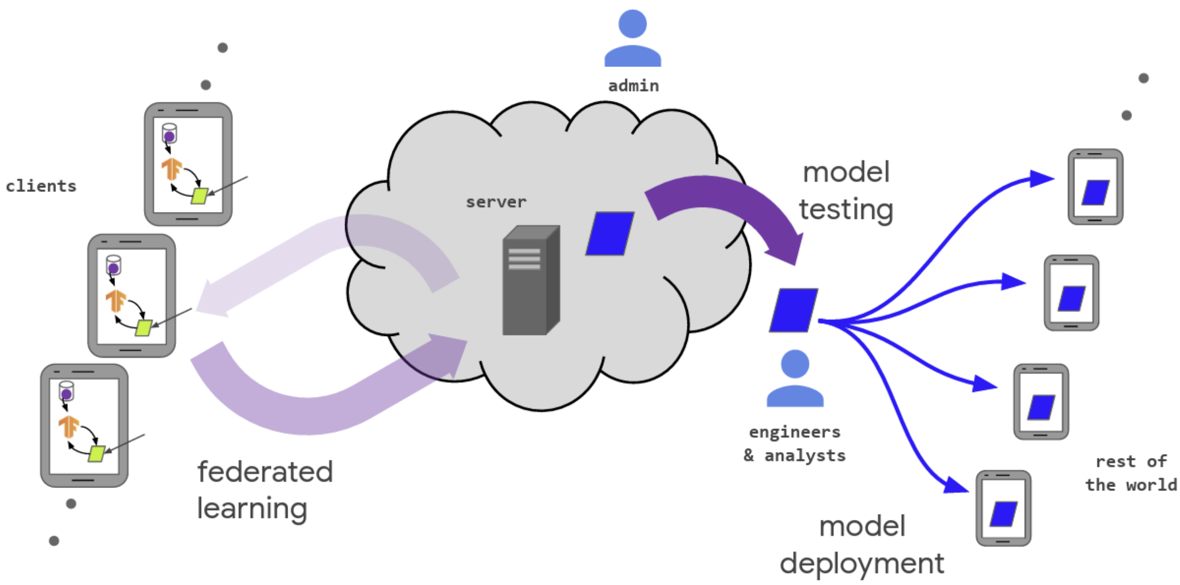

Figure 3. Lifecycle FL [25].

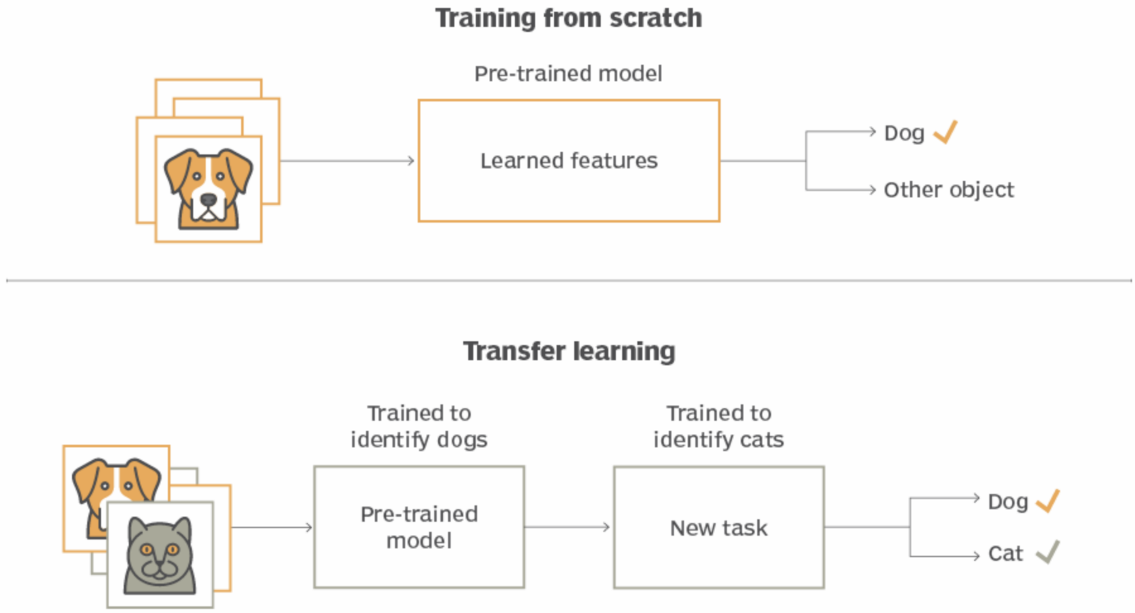

Figure 4. Detail TL [26].

Several previous studies have implemented FL in traditional traffic systems with feature engineering and ML [27], fan sound identification using decentralized microphones [28], real-time forest fire monitoring in fire-prone areas based on IoT [29], and smart farming for classifying crops based on climate [30].

2.3. Transfer Learning

Transfer learning (TL) is a concept in ML and Deep Learning (DL) where the weights of one model are used to enhance the performance of another model [22,23] In the context of neural networks, TL involves utilizing a model that is typically trained on a large dataset as an initial step for solving a new task. The pre-trained model can be used to extract features, where the early layers capture fundamental image features common across various datasets, while the final layers are fine-tuned to meet specific needs [31]. Figure 4 will illustrate how TL works.

Previous research successfully applied TL in acoustic-based machine condition monitoring using predictive methods with vibration or visual imagery [33], classification of waste to reduce manual labor in the recycling process [34], and in the healthcare sector, it has also been implemented in brain tumor cases [35].

2.4. Generative Adversarial Network (GAN)

GAN is an architecture in GAN that trains two neural networks to generate new data that is more authentic than the provided training dataset. GAN is referred to as adversarial because it involves training two opposing networks. The first network is tasked with generating new data by sampling from the input data and modifying it as optimally as possible. Meanwhile, the second network's role is to predict whether the generated data belongs to the original dataset or not. In other words, the second network evaluates the authenticity of the generated data. This process continues with a system that gradually produces fake data that closely resembles the original data, until the predictor network can no longer distinguish between fake and real data. Figure 5 illustrates how GAN works.

Previous studies have successfully applied GAN in cases of medical image restoration with low resolution, improving the quality of X-ray images and simultaneously classifying diseases, particularly in COVID-19 cases [36], It has also been used to impute missing electricity data based on clustering [37], In the medical field, GAN has proven effective in early diagnosis of glaucoma, a condition that can damage the optic nerve and lead to irreversible vision loss [38].

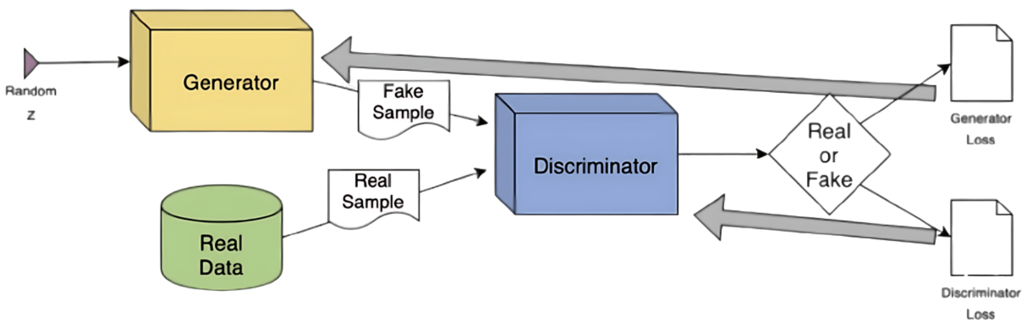

Figure 5. Concept GAN [39].

Table 1. Summary of Previous Research

Title	Author	Year	Methodology	Findings
XAI for Bird Species Image Classification	S. V. S. Kumar & H. K. Kondaveeti	2024	XAI for ecological research	XAI enhances transparency and accuracy in bird species classification.
FL for Crop Classification in Smart Farming	G. Idoje et al.	2023	FL for decentralized crop classification	FL enables efficient plant classification while maintaining data privacy.
TL for Brain Tumor Classification	S. Matin Malakouti et al.	2024	TL for medical image classification	TL improves accuracy in brain tumor classification using limited datasets.
GAN for Glaucoma Diagnosis	I. Govindharaj et al.	2025	GAN for medical image synthesis	GAN enhances early glaucoma diagnosis by generating high-quality medical images.
XAI for Medical Image Diagnosis	L. Weber et al.	2023	XAI	XAI helps doctors understand model decisions in medical diagnoses.
FL for IoT-Based Health Monitoring	A. Siddique et al.	2024	FL	FL allows real-time health monitoring while preserving patient privacy.
TL for Wildlife Image Classification	T. Murai et al.	2023	TL	TL improves accuracy in wildlife image classification.
GAN for Synthetic Data Generation in Autonomous Driving	J. Hwang et al.	2024	GAN	GAN generates synthetic data for autonomous vehicle system training.
XAI for Fraud Detection in Financial Transactions	S. Ali et al.	2023	XAI	XAI enhances fraud detection by explaining model decisions.
FL for Smart City Traffic Management	Z. Jin et al.	2024	FL	FL optimizes traffic management with decentralized data.
TL for Plant Disease Detection	J. Tanvir et al.	2025	TL	TL improves plant disease detection with small datasets.
GAN for Image Restoration in Historical Document Analysis	M. Ahishali et al.	2024	GAN	GAN restores damaged historical document images.
XAI for Sentiment Analysis in Social Media	F. E. Ayo et al.	2024	XAI	XAI enhances sentiment analysis by explaining model decisions.
FL for Personalized Healthcare Recommendations	K. N. Neuhäusler et al.	2024	FL	FL provides personalized health recommendations while safeguarding data privacy.
TL for Remote Sensing Image Classification	C. Geiß et al.	2023	TL	TL enhances remote sensing image classification.
GAN for Video Frame Interpolation in Surveillance Systems	R. Sekhar et al.	2024	GAN	GAN generates missing video frames for surveillance systems.
XAI for Credit Scoring in Banking	A. P. Verma Rishi	2023	XAI	XAI improves transparency in credit scoring.
FL for Energy Consumption Prediction	J. Hwang & D. Suh	2024	FL	FL predicts energy consumption with decentralized data.
TL for Speech Emotion Recognition	X. Kang	2025	TL	TL improves emotion recognition from voice.
GAN for Synthetic Data Generation in Medical Imaging	I. Govindharaj et al.	2025	GAN	GAN generates synthetic data for medical diagnosis training models.

XAI for Anomaly Detection in Industrial IoT	C. S. Wickramasinghe et al.	2021	XAI	XAI detects anomalies in industrial IoT systems with clear explanations.
FL for Real-Time Fire Detection	A. A. Siddique et al.	2024	FL	FL detects forest fires in real-time using decentralized data.
TL for Facial Expression Recognition	Y. Inoue et al.	2023	TL	TL improves facial expression recognition accuracy.
GAN for Data Augmentation in Natural Language Processing	F. Zhuang et al.	2021	GAN	GAN generates synthetic text data for training NLP models.
XAI for Predictive Maintenance in Manufacturing	L. Weber et al.	2023	XAI	XAI enhances machinery failure prediction with model decision explanations.
XAI for Climate Change Prediction	R. Yang et al.	2024	XAI	XAI improves climate change prediction with decision explanations.
FL for Smart Grid Optimization	Z. Zhang et al.	2023	FL	FL optimizes electrical grid management with decentralized data.
Combining Pre-Trained GAN Models for Skin Cancer Detection	A. Patel et al.	2024	Pre-Trained GAN Models and Max Voting Ensemble	TL utilizes pre-trained models. TL is used to leverage knowledge from models trained on large datasets (like ImageNet) and fine-tune them on specific datasets, such as skin cancer.
GAN to Synthetic Financial Scenarios Generation	M. Rizzato et al.	2023	GAN	GAN generates synthetic data for financial predictions.
XAI for Autonomous Vehicle Navigation	H. Tahir et al.	2024	XAI	XAI enhances interpretability in autonomous vehicle AI systems.
Privacy Preserving ML With Federated Personalized Learning in Artificially Generated Environment	M. Hosain et al.	2024	Adaptive Personalized Cross-Silo FL with Homomorphic Encryption (APPLE+HE)	APPLE+HE ensures privacy in personalized FL settings within artificially generated environments.
Deep TL for Agricultural Yield Prediction	A. Joshi et al.	2025	Deep TL	Deep TL for crop yield prediction using climate records and satellite imagery time-series data.
GAN for Synthetic Medical Data Generation	Y. Chen et al.	2022	GAN	GAN generates synthetic medical data for training diagnosis models.
XAI for Cybersecurity	P. Sharon Femi et al.	2023	XAI	XAI enhances cybersecurity threat detection with clear explanations.
FL for Energy Efficiency in IoT	M. Baqer	2025	FL	FL improves energy efficiency in IoT systems.
TL for Speech Recognition	D. Sasikala, S. Fazil	2025	TL	TL improves speech-to-text transcription.
GAN for Synthetic Wellbore Data	F. Chen et al.	2024	GAN	GAN generates synthetic wellbore data.
XAI for Predictive Policing	N. Klyuchnikov et al.	2023	XAI	XAI enhances crime prediction with transparent explanations.
FL for Disaster Response	B. Yurdem et al.	2024	FL	FL enables faster disaster response using decentralized data.
TL for Drug Discovery	A. Dalkiran et al.	2023	TL	TL enhances drug discovery efficiency.
GAN for Synthetic Data in Marketing	B. Vega-Márquez et al.	2024	GAN	GAN generates synthetic data for marketing analysis.
XAI for Driven Financial Transaction Fraud Detection	C. Sai et al.	2023	XAI and Deep Neural Networks	XAI improves the interpretability of fraud detection models, allowing

				financial analysts to understand the reasoning behind model predictions.
FL for Smart Home Automation	R. Al-Huthaifi et al.	2024	FL	FL optimizes smart home automation with decentralized data.
TL for Wildlife Conservation	H. Kath et al.	2024	TL	TL improves wildlife monitoring.
GAN in smart farming by using variational autoencoder and generative adversarial network	Y. Akkem et al.	2024	GAN	GAN generates synthetic data for plant recommendation systems.
A Comprehensive Framework for Transparent and XAI Sensors in Healthcare	R. Bouderhem	2024	XAI	XAI integrates transparency and explainability into AI sensor systems in healthcare.
FL for Smart Transportation	R. Gupta et al.	2024	FL	FL optimizes transportation management with decentralized data.
TL for Natural Language Processing	M. Omar et al.	2024	TL	TL enhances NLP model performance.
GAN for Synthetic Data in Environmental Monitoring	F. Ramzan et al.	2024	GAN	GAN generates synthetic data for environmental monitoring.
XAI for customer segmentation in product development	X. Hu et al.	2023	XAI	XAI improves customer behavior analysis with clear explanations.

3. Previous Research

Here is an example of filling in the table and an explanation for the Previous Research section. We will fill the table with several examples of previous research relevant to the topic of ML and classification, along with a brief description for each study. More details are shown in Table 1.

Description of Table 1 In Previous Research:

- **XAI for Bird Species Image Classification**
  This study utilizes XAI to enhance transparency in bird species image classification. XAI helps researchers understand how the model makes decisions, thereby increasing trust in the classification results [22].
- **FL for Crop Classification in Smart Farming**
  This study applies FL to classify crops in smart agriculture. FL enables data analysis from various farmers without centralizing the data, thus preserving data privacy. The results indicate that FL can classify crops with high accuracy while minimizing the risk of data leakage [30].
- **TL for Brain Tumor Classification**
  This study utilizes TL to classify brain tumors from medical images. A pre-trained model on a large dataset is used to extract features from medical images, which are then fine-tuned for the brain tumor classification task. The results demonstrate that TL can enhance classification accuracy even with limited datasets [35].
- **GAN for Glaucoma Diagnosis**
  This study uses GAN to generate high-quality medical images used in the early diagnosis of glaucoma. GAN helps improve diagnostic accuracy by providing realistic synthetic data [38].
- **XAI for Medical Image Diagnosis**
  This study uses XAI to assist doctors in understanding the model's decisions in medical diagnosis. XAI provides clear explanations of how the model identifies diseases from medical images, thereby increasing trust in AI systems in the healthcare field [20].
- **FL for IoT-Based Health Monitoring**
  This study applies FL for IoT-based health monitoring. FL enables real-time data analysis from various medical devices without centralizing the data, thereby maintaining patient privacy. The results show that FL can improve the accuracy of health monitoring while ensuring data security [29].
- **TL for Wildlife Image Classification**
  This study utilizes TL to improve the accuracy of wildlife image classification. A pre-trained model on a large dataset is used to extract features from wildlife images, which are then fine-tuned for the classification task. The results demonstrate a significant improvement in accuracy [31].
- **GAN for Synthetic Data Generation in Autonomous Driving**
  This study employs GAN to generate synthetic data used in training autonomous vehicle systems. This synthetic data helps address the issue of limited real-data, especially in hazardous or hard-to-replicate scenarios [37].

- **XAI for Fraud Detection in Financial Transactions**
  This study utilizes XAI to enhance fraud detection in financial transactions. XAI provides clear explanations of how the model identifies fraudulent transactions, thereby increasing trust in the fraud detection system [19].
- **FL for Smart City Traffic Management**
  This study applies FL to optimize traffic management in smart cities. FL enables the analysis of data from various traffic sensors without centralizing the data collection, thereby improving efficiency and reducing congestion [27].
- **TL for Plant Disease Detection**
  This study utilizes TL to enhance plant disease detection. A pre-trained model on a large dataset is used to extract features from plant images, which is then fine-tuned for the disease detection task. The results show a significant improvement in accuracy [34].
- **GAN for Image Restoration in Historical Document Analysis**
  This research utilizes GAN to restore damaged historical document images. GAN generates high-quality images that can be used for historical document analysis, enhancing the quality and accuracy of the analysis [36].
- **XAI for Sentiment Analysis in Social Media**
  This study utilizes XAI to enhance sentiment analysis on social media. XAI provides clear explanations of how the model classifies sentiment, thereby increasing confidence in the analysis results [16].
- **FL for Personalized Healthcare Recommendations**
  This study applies FL to provide personalized health recommendations while ensuring patient data privacy. FL enables data analysis from multiple sources without centralizing the data, thereby enhancing data security [28].
- **TL for Remote Sensing Image Classification**
  This study utilizes TL to enhance remote sensing image classification. A pre-trained model on a large dataset is used to extract features from satellite images, which are then fine-tuned for the classification task. The results show a significant improvement in accuracy [10].
- **GAN for Video Frame Interpolation in Surveillance Systems**
  This study uses GAN to generate missing video frames in surveillance systems. GAN enhances video quality by filling in the missing frames, thereby improving the effectiveness of the surveillance system [33].
- **XAI for Credit Scoring in Banking**
  This study utilizes XAI to enhance transparency in credit assessment. XAI provides clear explanations of how the model evaluates creditworthiness, thereby helping banks understand the model's decision-making process [18].
- **FL for Energy Consumption Prediction**
  This study applies FL to predict energy consumption using decentralized data. FL enables data analysis from various sources without the need to centralize the data, thereby enhancing energy efficiency [37].
- **TL for Speech Emotion Recognition**
  This study utilizes TL to enhance the accuracy of emotion recognition from speech. A pre-trained model on a large dataset is used to extract features from the speech, and then fine-tuned for the emotion recognition task. The results demonstrate a significant improvement in accuracy [3].
- **GAN for Synthetic Data Generation in Medical Imaging**
  This study utilizes GAN to generate synthetic data used in training medical diagnosis models. This synthetic data helps address the issue of data scarcity, particularly in the case of rare diseases [38].
- **XAI for Anomaly Detection in Industrial IoT**
  This study uses XAI to detect anomalies in industrial IoT systems. XAI provides clear explanations of how the model identifies anomalies, thereby enhancing trust in the detection system [9].
- **FL for Real-Time Fire Detection**
  This study applies FL to detect forest fires in real-time using decentralized data. FL enables data analysis from various sensors without the need to centralize data collection, thereby enhancing detection speed [29].
- **TL for Facial Expression Recognition**
  This study employs TL to improve facial expression recognition accuracy. A pre-trained model on a large dataset is used to extract features from facial images, which are then fine-tuned for the expression recognition task. The results show a significant improvement in accuracy [31].
- **GAN for Data Augmentation in Natural Language Processing**
  This study utilizes GAN to generate synthetic text data used in training NLP models. This synthetic data helps address the issue of insufficient real data, particularly in tasks such as translation and sentiment analysis [32].
- **XAI for Predictive Maintenance in Manufacturing**
  This study utilizes XAI to enhance the prediction of machine failure in manufacturing. XAI provides clear explanations of how the model predicts machine failure, thereby assisting technicians in taking preventive actions [20].
- **XAI for Climate Change Prediction**
  This study utilizes XAI to predict climate change by providing transparent explanations of how the model makes decisions. The XAI method helps scientists understand the key factors influencing climate change, such as carbon emissions, global temperature, and weather patterns. The results show that XAI not only

enhances prediction accuracy but also provides actionable insights for climate change mitigation [40].

- **FL for Smart Grid Optimization**
This study applies FL to optimize the management of electrical grids by utilizing decentralized data from various sources, such as households, industries, and power plants. FL enables data analysis without the need to aggregate data centrally, thus preserving user privacy. The results demonstrate improved energy efficiency and reduced operational costs [41].
- **Combining Pre-Trained GAN Models for Skin Cancer Detection**
This study demonstrates that the combination of pre-trained GAN models and the Max Voting Ensemble technique is an effective approach to enhance the accuracy and reliability of skin cancer detection. By leveraging TL and ensemble learning, this model can provide more accurate and reliable predictions, which in turn can improve treatment outcomes and reduce mortality rates [42].
- **GAN to Synthetic Financial Scenarios Generation**
This study employs GANs to generate realistic synthetic financial scenarios. By generating high-quality synthetic data, GANs can enhance risk analysis, model testing, and financial market simulations. Although XAI, FL, and TL are not explicitly mentioned in the title or summary provided, these three techniques can serve as valuable complements to improve the security, efficiency, and interpretability of AI systems in the financial context. [43].
- **XAI for Autonomous Vehicle Navigation**
This study focuses on the development of a hybrid XAI solution for autonomous vehicles by integrating LIME and SHAP. Although FL, TL, and GAN are not explicitly mentioned in the title or abstract provided, these three techniques can serve as valuable complements to enhance the security, efficiency, and performance of AI systems in the context of autonomous vehicles [44].
- **FL for Personalized Education**
This study explains that the APPLE+HE algorithm has emerged as a strong recommendation for ML tasks that preserve privacy in artificially generated environments within federated personalized learning settings [45].
- **Deep TL for Agricultural Yield Prediction**
This study employs Deep TL as an effective approach to enhance the accuracy of crop yield predictions. By leveraging pre-trained models and fine-tuning them on agriculture-specific datasets, prediction accuracy can be significantly improved while reducing training time and costs. This approach holds great potential for enhancing agricultural management & food security [46].
- **GAN for Synthetic Medical Data Generation**
This study utilizes GAN, a technique that is effective for medical image augmentation. By generating realistic synthetic images, GANs can enhance both the quality and quantity of training datasets, which in turn improves the performance of AI models in medical applications [47].
- **XAI for Cybersecurity**
This research utilizes XAI to enhance cyber threat detection by providing clear explanations of the model's decisions. XAI helps security analysts understand how the model identifies threats, thereby improving the response to cyberattacks [48].
- **FL for Energy Efficiency in IoT**
This study applies FL to enhance energy efficiency in IoT systems. FL enables data analysis from various IoT devices without centralizing the data, thereby reducing energy consumption and improving system performance [49].
- **TL for Speech Recognition**
This research utilizes TL to enhance the quality of speech-to-text transcription. By leveraging pre-trained models and fine-tuning them on domain-specific datasets, transcription accuracy can be significantly improved while reducing training time and costs. This approach holds great potential for enhancing communication systems across various applications, including healthcare, law, and customer service [50].
- **GAN for Synthetic Wellbore Data**
This study uses GAN to generate realistic synthetic borehole data. However, the evaluation of synthetic data quality must consider both mathematical metrics and expert perception to ensure that the data is useful in practical applications. This approach can enhance the quality and acceptance of synthetic data in the oil and gas industry [51].
- **XAI for Predictive Policing**
This study utilizes XAI to enhance crime prediction by providing transparent explanations of the model's decisions. XAI helps law enforcement understand the factors influencing crime predictions, thereby improving the effectiveness of preventive measures [52].
- **FL for Disaster Response**
This study implements FL to enable faster disaster response by utilizing decentralized data from various sources. FL allows data analysis without centralizing the data, thereby enhancing the speed and efficiency of disaster response [53].
- **TL for Drug Discovery**
This study utilizes TL to enhance the efficiency of drug discovery by leveraging pre-trained models on large datasets. TL enables the identification of potential compounds more quickly and accurately [54].
- **GAN for Synthetic Data in Marketing**
This study uses GAN to generate synthetic data for marketing analysis. This synthetic data helps address the issue of data scarcity, particularly in situations

where marketing data is difficult to obtain. The results show that models trained with synthetic data can provide accurate analysis [55].

- **XAI for Driven Financial Transaction Fraud Detection**
  This study employs XAI to enhance the interpretability of fraud detection systems in financial transactions. Although FL, TL, and GAN are not explicitly mentioned in the title or abstract, these three techniques could serve as valuable complements to improve the security, efficiency, and performance of fraud detection systems [56].
- **FL for Smart Home Automation**
  This study applies FL to optimize smart home automation by utilizing decentralized data from various IoT devices. FL enables data analysis without the need to centralize data collection, thereby enhancing both efficiency and privacy [57].
- **TL for Wildlife Conservation**
  This study utilizes TL to enhance wildlife monitoring by leveraging pre-trained models on large datasets. TL enables more accurate identification and tracking of wildlife [58].
- **GAN in smart farming by using variational autoencoder and gen-erative adversarial network**
  This study utilizes GAN to present the proposed model architecture and training process, evaluating the quality and utility of the synthetic data generated through various experiments, including visualizations such as heatmaps, scatter plots, cumulative count diagrams per feature, and distribution diagrams per feature. The results of this study have the potential to make a significant contribution to the field of agriculture by providing a reliable and abundant source of training data for Crop Recommendation (CR) systems [59].
- **A Comprehensive Framework for Transparent and XAI Sensors in Healthcare**
  This study proposes a comprehensive framework for integrating transparency and explainability into AI sensor systems in the healthcare sector. The framework is designed to enhance trust, accuracy, and regulatory compliance, enabling safer and more effective AI applications in healthcare services. This research can serve as a guide for developers, researchers, and practitioners in designing responsible and reliable AI systems [60].
- **FL for Smart Transportation**
  This study applies FL to optimize transportation management by leveraging decentralized data from various sources, such as vehicles, traffic lights, and road sensors. FL enables data analysis without centralizing the data, thereby enhancing efficiency and reducing traffic congestion [15].
- **TL for Natural Language Processing**
  This research employs TL to enhance the performance of Natural Language Processing (NLP) models by leveraging pre-trained models on large datasets. TL enables improved accuracy in NLP tasks, such as translation and sentiment analysis [61].
- **GAN for Synthetic Data in Environmental Monitoring**
  This study utilizes GAN to generate synthetic data used in environmental monitoring. This synthetic data helps address the issue of data scarcity, particularly in situations where real-world environmental data is difficult to obtain. The results indicate that models trained with synthetic data can provide accurate analysis [62].
- **XAI for customer segmentation in product development**
  This study utilizes XAI to enhance customer behavior analysis by providing clear explanations of model decisions. XAI helps marketers understand the factors influencing customer behavior, thereby improving the effectiveness of marketing campaigns [63].

4. Future Challenges, Opportunities and Implementation

In the era of Technology 5.0, ML continues to show significant advancements across various sectors. This research aims to examine current trends in ML classification, focusing on four main approaches: XAI, FL, FL, and GAN. The methods applied include a comprehensive literature review of research from Asia and experiments with related datasets. The research findings indicate that XAI can enhance transparency and accuracy in data classification, FL enables decentralized learning while preserving data privacy, TL improves accuracy on small datasets, and GAN assists in data augmentation for better training models. In conclusion, these techniques not only enhance the efficiency and accuracy of classification but also open up new opportunities for innovation across various fields, including healthcare, transportation, and cybersecurity.

Despite the significant innovations that ML 5.0 brings to classification techniques, several challenges remain to be addressed. One major challenge is the interpretability and transparency of models. With the increasing complexity of algorithms, such as Transformer-based GAN and multimodal models, understanding how decisions are made has become increasingly difficult. This raises concerns in fields such as medicine, law, and finance, where transparency is crucial. Additionally, bias in data and models remains a major issue. Some studies in this review show that datasets used to train models are often not sufficiently representative, leading to biased classification results that are unfair to certain groups. Another emerging challenge is computational efficiency and sustainability. Larger classification models require significant computational power, which leads to high energy consumption. With growing awareness of the environmental impact of AI technologies, there is a pressing need to develop models that are more energy-efficient, both in terms of algorithms and computational infrastructure. Furthermore, regulatory and ethical challenges surrounding AI are under the spotlight. The adoption of ML 5.0 in various industries requires clear guidelines and standards to ensure its use remains safe, accurate, and does not cause negative repercussions.

Behind the challenges, ML 5.0 also opens up new opportunities in the field of data classification. One of the most promising is its integration with other technologies, such as Quantum Computing, the Internet of Things (IoT), and Edge AI. Several articles in this review highlight that the use of Quantum ML (QML) has the potential to improve data processing efficiency in classification, particularly in cases involving high-dimensional data. Additionally, the use of FL and TL in classification paves the way for safer and more flexible data processing. With FL, data can remain on user devices without being sent to a central server, thereby enhancing privacy and security. On the other hand, TL enables models that have been trained in one domain to be easily adapted to another domain with a small amount of additional data, reducing the need for large datasets, which often pose a challenge in developing new models. In the industrial sector, ML 5.0 also opens new opportunities to enhance operational efficiency. The application of generative AI in classification allows models not only to classify data but also to create new representations of data that can be used for simulation, medical diagnosis, and product development. With AI trends moving toward self-supervised and adaptive models, future classification models will no longer rely entirely on labeled data but can learn from available data patterns, enabling higher efficiency across various sectors, including manufacturing, healthcare, and finance.

The implementation of ML 5.0 in classification systems has shown promising results across multiple fields. In the medical field, research indicates that the combination of GAN and XAI has improved diagnostic accuracy for diseases based on medical imaging. One study reviewed revealed that Transformer-based models applied in radiology were able to detect cancer with higher accuracy compared to conventional approaches. In the transportation and smart city sectors, ML 5.0 enables more advanced classification systems for predicting traffic congestion, traffic management, and vehicle anomaly detection. With the combination of Edge AI and IoT, classification can be performed in real-time on smaller devices without relying on the cloud, thus improving speed and processing efficiency. Additionally, in the financial industry, generative AI-based classification models have been used to detect suspicious transaction patterns, helping to improve fraud detection systems with higher accuracy. Several studies reviewed show that the application of Self-Supervised Learning (SSL) models in anomaly detection has reduced false positive rates in fraud detection by up to 30%, providing a more accurate solution for the finance and banking sectors. Going forward, the implementation of ML 5.0 in classification systems will increasingly rely on collaboration between industries, academia, and regulators. The adoption of ethical AI standards and the enhancement of transparency in models will be key to ensuring that this technology can be widely utilized with a positive impact on society.

5. Conclusion and Discussion

The application of AI techniques across various domains continues to experience significant advancements. XAI, for instance, provides greater transparency in AI model decision-making processes. In tasks like bird species image classification and medical diagnostics, XAI allows researchers and professionals to understand the reasoning behind the decisions made by the model, which is crucial in contexts that require high accuracy and have a significant impact on human health. In the financial sector, the use of XAI in fraud detection helps increase consumer trust and minimize the risk of misidentification errors.

Meanwhile, FL presents an innovative solution for safeguarding data privacy, which is increasingly essential in today's digital era. The use of FL in smart agriculture, for example, enables farmers to train crop yield prediction models without sharing their personal or sensitive data with third parties. In the context of IoT and healthcare monitoring, FL supports the processing of medical data more securely and efficiently, given the importance of patient privacy in AI-driven medical decision-making. However, the main challenge that persists is ensuring the consistency and quality of the data generated by these decentralized models.

Regarding TL, this technique is highly beneficial for enhancing accuracy in applications that require image or speech processing, which often demands large amounts of training data. In brain tumor classification, for example, TL allows the use of models trained on large datasets to be applied to smaller, domain-specific medical datasets, improving training efficiency and yielding more accurate predictions. The success of TL paves the way for broader AI applications in various medical and agricultural fields, where data availability is limited. Meanwhile, GAN, with their ability to generate realistic synthetic data, have proven highly beneficial in data augmentation. In the medical field, GAN is used to generate synthetic medical images that can be employed to train models for better disease diagnosis without requiring original patient data. This also applies in the context of historical document restoration, where GAN helps generate copies of lost or damaged documents. However, the use of GAN also demands strict supervision due to the potential for misuse in generating fraudulent data that could compromise information integrity. The combination of these techniques, such as XAI, FL, TL, and GAN, continues to open significant opportunities for accelerating innovation in real-world AI applications. Although challenges such as privacy, model bias, and data limitations remain concerns, the development of these technologies indicates a positive direction toward improving the efficiency, transparency, and accuracy of AI systems.

In the future, the application of these techniques is expected to offer better solutions to various challenges faced by industries, finance, cybersecurity, and climate change mitigation, with great potential to advance a more inclusive and responsible AI technology.

6. Conflicts of Interest

The authors declare no conflicts of interest.

7. References

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