Artificial Intelligence in Edge-Based IoT Applications

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Given its advantages in low latency, fast response, context-aware services, mobility, and privacy preservation, edge computing has emerged as the key support for intelligent applications and 5G/6G Internet of things (IoT) networks. This technology extends the cloud by providing intermediate services at the edge of the network and improving the quality of service for latency-sensitive applications. Many AI-based solutions with machine learning, deep learning, and swarm intelligence have exhibited the high potential to perform intelligent cognitive sensing, intelligent network management, big data analytics, and security enhancement for edge-based smart applications.

Internet of things | edge computing | artificial intelligence

1. Smart Environment

Intelligent environmental monitoring aims to establish a full system that incorporates several types of sensors and internet of things (IoT) devices designed to measure various indications of the environment, such as temperature, humidity, and the concentration of pollutants in the air or the water. The integration of artificial intelligence and edge computing is essential to meet the requirements related to the complexity and the huge amount of environmental data that can be collected in this context.

1.1. Air Quality Monitoring (AQM)

For the optimal utilization of cloud resources and the improvement of computational power, a distributed fog computing framework for air-quality monitoring was developed in [1] by applying data preprocessing and clustering techniques to identify outliers on the fog layer by using the K-means algorithm and feeding only the relevant information to the cloud for the classification phase. This approach achieves *95%* accuracy with SVM compared to a multilayer perceptron (MLP), decision tree (DT), K-nearest neighbor (KNN), and naive Bayes (NB), and reduces the amount of data sent to the cloud still improving the response time.

In order to improve the computational efficiency and model performance of the environmental monitoring system considering regional characteristics when distributing various site monitoring models, the authors in [2] proposed a new framework called federated region-learning based on edge computing for PM2:5 air-quality monitoring. The authors first applied a regionalization algorithm that divides the monitoring locations into a set of subregions, each designed by microclouds in which the regional model is selected by the model that has the highest accuracy and, subsequently, the global model is aggregated by using two types of aggregation strategies to target the different bandwidth requirements better. The evaluation of the platform has been tried by using recurrent neural networks (RNNs) and convolutional neural networks (CNNs). It has been proven that the FRL approach improves the computational efficiency compared to the centralized training mode and normal federated learning (FL) [3].

In [4], Wardana et al. designed a distributed short-term air-quality prediction system for hourly PM2.5 concentrations based on a hybrid deep learning model composed of 1D CNN and long short-term memory networks (CNN-LSTM). They conceived an efficient posttraining quantization method to optimize the LSTM model and make it usable by resource-constrained edge devices wherein a one-dimensional CNN is used as a feature extractor. Through the results, the authors claim that the model has proven its performance in reducing execution time and latency.

In order to ensure privacy and reduce network traffic, the authors in [5] designed an efficient collaborative edge/cloud framework to predict the future concentration of fine particles in an individual space by selecting the best predictive model for the local edge based on its characteristics. The edge selects from the cloud the model with the highest correlation for a specific factor instead of choosing the model with the best performance. The system's performance is validated with the LSTM algorithm for indoor PM10 and PM2.5 status prediction.

For efficient data generation and privacy preservation for PM2.5 predictions, Putra et al. in [6] proposed a federated compressed learning based on an edge computing framework for massive-scale wireless sensor networks (WSNs). This approach used compressed sensing techniques at the sensor level to reduce network data traffic. Then, at the fog layer, the data is trained distributively. After that, the global model is constituted by aggregating the local training models at the cloud layer. The evaluation is performed using LSTM for PM2.5 concentration prediction and shows the efficiency of the compression sensing in reducing the data at the computation efficiency of the proposed model.

1.2. Water Quality Monitoring (WQM)

In order to continuously monitor water quality in a distributed manner by using low-cost, cost-effective sensors, the authors of [7] developed an on-board sensor classifier for detecting water pollutants. First, they used the principal component analysis (PCA) algorithm to simplify and transform the original sensed data into a 3D space. Then, an adaptive classification scheme is employed on the transformed space to distinguish the contaminants by using a simple geometric model, the parameters of which are learned by using a generational evolutionary algorithm (EA).

Authors in [8] developed a soft sensor model for real-time water-quality monitoring through intelligence at the edge to estimate the value of the biological oxygen demand. An edge/cloud platform is designed wherein the instance-based learning (IBK) algorithm is selected after a comparative study between different machine learning (ML) algorithms.

In [9], the authors proposed an online water-quality monitoring and early warning model based on edge computing. The authors proposed an improved backpropagation neural network (BPNN) by using a hybrid optimization method based on the Nelder–Mead simplex method and cuckoo search algorithm to optimize the weight and deviation of the BPNN.

1.3. Smart Water Management (SWM)

In [10], the authors designed an efficient framework for water conservation based on blockchain technologies, soft computing, and machine learning. At the edge nodes (house nodes) a feed-forward neural network (FFNN) trained by symbiotic organism search is used to forecast the water consumption of each house. Then, the forecast value is compared to the historical value obtained by using a randomized probability distribution model for neural networks called the mixture density network (MDN). Based on these two calculated values, an incentive system is prepared in the blockchain to assign a good incentive to houses using less water than the historical value and applies a penalty to houses using more water than expected. Several factors were used such as (i) the number of people, (ii) the average income of the family, (iii) the profession of the members, and (iv) previous water demands. Results show the effectiveness of the approach for optimal water management.

1.4. Underwater Monitoring (UWM)

Regarding marine environment monitoring, Yang et al. designed in [11] a fog/cloud-based framework for effectively managing ocean data and real-time monitoring of the marine environment. They introduced a fog layer to support data processing by using a numerical gradient-based method for data cleaning and an improved algorithm based on the evidence theory. This latter is used for multisensory information fusion with the aim of reducing the data volume and improving the data quality. In the cloud layer, a predictive model with BPNN is implemented. Authors argue that the framework can improve the efficiency of data use, improve the processing speed of ocean data and reduce the time delay. In [12], Lu et al. introduced a cognitive ocean network called motor anomaly detection system and detection of marine organisms. The proposed system consists of two methods: the first is deployed in the edge layer by using deep reinforcement learning and Raspberry Pi to prevent the default of underwater vehicles, and the second is deployed in the fog layer to detect marine organisms by using YOLO-based underwater method. Kwon et al. proposed in [13] a distributed deep learning (DL) approach based on federated learning with underwater IoT devices in the ocean environment. They used a multiagent deep deterministic policy gradient based on reinforcement learning (RL) to solve the problem of joint cell association and resource allocation in a way that improves the DL throughput of underwater IoT devices in underwater FL.

Regarding seawater quality prediction, Sun et al. developed in [14] a multivariate prediction model supported by edge computing for seawater quality assessment based on the combination of a PCA and relevance vector machine (RVM). Results show that the proposed model has higher prediction ability and less time consumption than other approaches.

2. Smart Grid

The integration of new technologies, such as IoT and artificial intelligence, into the power grid system allows (1) the design of a smart decision system support by developing an electricity distribution network. This offers the possibility of remotely measuring the state of the energy usage status online and thus enables the control of energy consumption and its further adjustment to the consumers' energy needs. It also allows (2) the identification of abnormal behaviors in the consumption or production of electrical energy, and (3) the prediction of future electricity demand and energy consumption in an intelligent way based on the data acquired by the smart meters.

2.1. Load/Demand Forecasting (LDF)

Taïk and Cherkaoui proposed in [15] an edge-based, short-term individual load-forecasting framework. They used a distributed computation that uses an FL approach with the aim of addressing the challenges presented by the stochastic nature of consumption profiles and privacy in the smart grid. The realized simulations show that the approach outperforms the centralized model in terms of reducing the network load while preserving the privacy of the consumption data. This work does not solve the problem of detecting anomalies in the power consumption profile, which affects the model's accuracy.

The authors in [16] proposed an edge-based short-term load-forecasting framework that uses an FL approach to enhance the prediction performance and reduce prediction errors. They proposed to group energy customers into similar users based on socioeconomic aspects or consumption similarities by using clustering techniques. This grouping of users is efficient, more effective than other trivial privacy-preserving schemes, and more adaptable to rapidly changing consumption patterns. Compared with the centralized system, the proposed approach is more efficient in terms of model learning time, scalability, and inherently privacy-friendly alternatives. Furthermore, the communication overhead is reduced when energy-consumption measurements are recorded at a fine granularity.

Li et al. proposed in [17] a fog computing-based incremental learning for real-time day-ahead prediction of building energy demands. In order to choose the most suitable incremental machine learning model to address the high-speed real-time requirements of fog computing and generate good and fast edge intelligence, the authors compared two incremental learning algorithms, namely the swarm decision table (SDT) and the classical decision Hoeffding tree. Both combined with swarm feature selection to deal with the complexity of aggregated IoT and select only the significant features for efficient incremental machine learning. Results show the effectiveness of the proposed model.

Li et al. also proposed in [18] a fog computing-based platform for real-time prediction of electricity demand. First, a clustering algorithm categorizes users based on their total electricity consumption. Then, according to the characteristic of users' historical electricity consumption, a predictive model using XGBoost or ARMA was selected. The accuracy of the proposed approach is *20%* higher than classical models.

In [19], Rabie et al. proposed a fog-based framework for accurate and fast electrical load forecasting in smart grids. First, a data summarization is performed on the collected data by applying several rules enabling the fog to send only the relevant data to the cloud by using fuzzy rank combined with a wrapper feature selection method and outlier detection. Then, an NB classifier is used to train the model and evaluate feature selection-based data processing techniques. Results show the effectiveness of the fog-based framework for accurate and fast load forecasting.

Luo et al. proposed in [20] a short-term energy prediction-based edge computing platform. It consists of four stages: (1) data acquisition and fusion performed on edge nodes to support redundant multisource heterogeneous IoT by using a semantic information model, (2) event data generating stage performed in the routing nodes to deal with the weak semantics of IoT data, (3) local aggregation performed on edge nodes in order to aggregate data based on its spatiotemporal semantics, and (4) a prediction model built in the central server by using an online deep neural network model which updates the prediction model in real time over the stream of data instances to accommodate the changes in the IoT environment.

The authors of [21] proposed a short-term energy consumption forecasting model named Energy-Net, optimized for deploying resources constrained devices. Energy-Net uses a deep learning approach that exploits the spatial and temporal learning capability to predict energy consumption.

In [22], the authors proposed a framework based on edge computing for short-term residential electricity demand forecasting by using online learning and reservoir computing by state network architecture to avoid high computational costs considering the nonlinear and dynamic behavior of demand time series improve the accuracy of the prediction model by continuously tracking the dynamically changing demand characteristics.

2.2. Demand-Side Management (DSM)

Cicirelli et al. proposed in [23] an edge-based energy management system to reduce the energy cost of daily household appliances. They proposed a load appliance scheduling algorithm that exploits reinforcement learning. It takes into account time variable profiles regarding energy cost, production of energy, and energy consumption of the appliances. The approach is validated through the implementation of a real-world use case that shows convincing results.

Tom et al. used in [24] a fog-based IoT architecture to design a smart energy management system and build a solution for demand reduction of individual houses in a locality during peak hours. They used autoregressive integrated moving average (ARIMA) to predict consumer utilization by studying consumers' daily usage patterns and a discriminant analysis to find the appliances playing a significant role.

Taik et al. proposed in [25] a multilevel prodecision framework based on federated learning for intelligent decision-making in energy markets. It prioritizes individual prosumer decisions supported by the 5G wireless network for rapid coordination between community members. Each prosumer forecasts energy production and consumption to make proactive business decisions taking into account collective-level demands. The result achieves high accuracy for different energy resources with low communication costs.

2.3. Load Anomaly Detection (LAD)

For providing real-time anomaly detection for solving big data issues in the power consumption domain, Jaiswal et al. [26] proposed a hierarchically distributed fog computing architecture for smart meter data analysis in households by using an ensemble method consisting of four lightweight regression models: linear regression (LR), support vector regression (SVR), random forest regression (RFR), gradient boosting regression (GBR).

Liu et al. designed a distributed fog computing platform for detecting smart meter data anomalies [27]. They used a stacked denoising autoencoder and KNN classifier deployed on the fog nodes. At the same time, an adaptive elitist GA is used to optimize the required computational task for supporting the model in the fog nodes and minimizing the communication cost.

Olivares–Rojas et al. proposed a detection of electric energy fraud supported by edge computing [28]. First, a dimensionality reduction by the PCA algorithm is used. Then, prediction techniques based on previously established patterns of energy consumption/production by LR, DT, neural networks, and MLP are performed.

Utomo and Hsiung developed in [29] a multitiered solution for efficient and fast real-time anomaly detection. They use a clustering model based on the combination of the K-means and hierarchical density-based spatial clustering of applications with noise (HDBSCAN) for data reduction. Then, the oversampling mechanism SMOTE is used to cover the imbalanced dataset. The authors compare support vector regression (SVR), KNN, and DNN to choose the best detector anomalies classifier.

In [30], Zhang et al. proposed a framework supported by the edge for energy theft detection. The detection passes through three stages: (1) feature learning based on load profile for energy consumption analysis is implemented by using VAE-GAN, (2) k-means clustering is used to determine the representative features of normal load profiles, and (3) abnormality degree is calculated by using a threshold-based abnormality detector.

In [31], the authors proposed a federated voting classifier for energy theft detection. The authors used a majority voting for the three classifiers (i.e., RF, KNN, and bagging classifier (BG)). Results show the effectiveness of the model compared to the centralized cloud model in terms of privacy.

3. Smart Agriculture

The integration of IoT technologies and edge computing creates great opportunities for the agricultural field. It makes up a support system that is able to monitor, capture and analyze information about crops and livestock in real-time. It may include early plant disease prevention, better soil monitoring and management, livestock management, and reduction of environmental impacts by climate change prediction. The use of artificial intelligence improves the production process, maintains the highest levels of crop quality, and reduces costs and waste.

3.1. Weather Prediction (WP)

Guillén et al. consider in their work [32] the construction of an automated decision-making framework for precision agriculture. In such problems, constraints, including low-bandwidth connectivity and energy consumption, must be addressed. To this end, the authors proposed an edge-based platform for the early identification of frost on crops by estimating the low temperatures through an LSTM model on edge devices. This helps farmers to obtain a temperature prediction in real-time. The proposed model is evaluated in terms of performance and power consumption of edge devices.

In [33], Kaur and Sood proposed a framework for drought forecasting. At the fog layer, a dimensionality reduction method based on PCA is used, although the classification of drought severity is performed on the cloud layer by using ANN with genetic algorithms (GA). After a fixed interval of time, the predicted values of drought severity are used by the ARIMA model for future drought forecasting.

3.2. Livestock Management (LM)

The authors of [34] suggested strategies for offloading computation from cloud to fog to assist the huge quantity of multimedia data from IoT devices in smart agriculture. They process more deep learning tasks at the fog layer by assigning the maximum number of layers on each fog node with the aim to (1) reduce the amount of data transferred to the cloud, (2) utilize resources efficiently, and (3) reduce network congestion. The authors show, through experiments, that the proposed strategies had satisfactory results in terms of bandwidth, number of deep learning tasks for each node, and the data volume transferred to the cloud compared with existing methods.

For accurate and early detection of lameness in smart dairy farming, Taneja et al. developed in [35] an application based on fog/cloud computing to collect activity data, monitor the cattle in real-time, and identify lame cattle at an early stage. They employed a K-means algorithm at the fog layer for data processing, and classification was done on the cloud by using the KNN algorithm. Results show that the application can detect lameness three days before the farmer can visually capture it with high accuracy and minimal communication cost.

3.3. Smart Irrigation (SI)

To improve irrigation water, Cordeiro et al. have proposed in [36] a fog-based framework for soil moisture forecasting. First, a KNN data imputation is used for the missing values to increase data reliability. Subsequently, an LSTM is used for the prediction by employing a small single-board computer.

In [37], authors proposed a low-cost intelligent irrigation system based on edge computing to forecast environmental factors. They used an LSTM/gated recurrent units (GRU)-based model for a comparative analysis by using many frameworks. Results show the reliability of LSTM and GRU for the prediction of environmental factors.

3.4. Crop Monitoring and Disease Detection (CMDD)

Identifying crop diseases is one of the most difficult tasks in smart agriculture.

A timely detection on crops to stop diseases from spreading was presented in [38]. The authors proposed a model named deep leaf, a coffee plant disease detector based on edge computing. It detects the main biotic stresses affecting crops. The proposed model uses a dynamic compression algorithm based on K-means for the reduction of a model footprint to reduce the complexity of the CNN model and run it on devices with limited hardware capabilities.

Likewise, the authors of [39] proposed an IoT monitoring framework for detecting tomato diseases. First, a pretraining model is constructed on the cloud by using VGG networks. Then, in order to fit the model on embedded mobile platforms, a depth-wise separable convolutional network is used to reduce the parameters of the model and calculation of model feature extractor. The experimental results show that the framework can accurately detect crop diseases in less time.

Zhang and Li proposed in [40] an adaptive sensing strategy for the crop life cycle based on edge computing. First, the growth stage of the crop is divided by the Gath–Geva fuzzy clustering for the sensing nodes. Then, data-driven algorithms are used in the edge server to extract and optimize the key parameters corresponding to the growth stage in order to increase the data values by reducing redundancy and improving the correlations between the sensing data. Finally, a neural network-based crop growth stage prediction model is performed.

3.5. Monitoring the Health Status of Agriculture Machines (MHSAM)

Gupta et al. proposed in [41] an edge-based framework for agriculture vehicle health monitoring by using ANN. To decrease the model's complexity in terms of computing and develop a lightweight one that can be deployed on a smartphone, two levels of optimization using a genetic algorithm for ANN are conducted.

In [42], Rajakumar et al. proposed a framework to identify the health condition of the vehicles. They design a fault-detection algorithm by using a deep convolutional neural network (DCNN) on smartphones. The authors used the Levy flight optimization algorithm (LFOA) to optimize the network structure of the DCNN, minimize the number of neurons in the DCNN hidden layer, minimize the number of input features from the audio recordings, and enhance the classification accuracy.

4. Smart Education

Smart education is defined as the integration of IoT devices with learning that can establish location information, motion sensing, and visual recognition tools. IoT devices in combination with other technologies such as artificial intelligence and cloud computing are used to evaluate educators' engagement and skills and improve the teaching and learning expertise in the field. Using edge computing in smart education: (1) reduces the delay, (2) improves the level of service delivery for learners by protecting information transmitted, (3) and guarantees that every communication process is managed effectively [43].

4.1. Student Engagement Monitoring (SEM)

Umarale et al. proposed in [44] an edge computing-based deep learning technique for detecting and identifying the attention level of learners within online learning sessions. They employed, on edge devices, a lightweight CNN model that uses facial image data to determine the attention level. The output is further processed on the cloud to derive an attention average of the participants. Then, the attention average is reported to the host, helping the teachers to obtain information about the students' performances and further helping them identify the students who were inattentive during the session.

Li et al. designed in [45] a real-time intervention system for negative emotional contagion in the classroom based on edge computing infrastructure. The system integrates an emotional contagion model with a deep learning algorithm. To achieve multiperson emotional recognition, an embedded device is used to process images to recognize the emotions of all the students in the classroom and locate the source of the negative emotion to take real-time intervention actions through visual emotion identification.

In [46] Preuveneers et al. introduced a learning management system for engagement monitoring by using a collaborative edge-cloud framework. They combine FL with secure multiparty computation to process users' behavior data to analyze student involvement and increase the online learning system to the next level.

In [47] to enhance students' independence in resolving difficult engineering problems and boost their marketability, authors created an experimental open-source distance learning platform based on edge computing and artificial intelligence that is well-suited for distance learning.

The authors in [48] proposed a framework for monitoring student stress and generating real-time alerts to predict student stress. The authors used Visual Geometry Group (VGG16) for facial expression, bi-LSTM for speech texture analysis, and multinomial NB techniques to generate emotion scores and classify stress events as normal or abnormal.

4.2. Skill Assessment (SA)

Sood and Singh proposed in [49] an e-learning framework with multiple functional aspects. The proposed framework helps in enhancing the skill set of students. The first aspect is that of monitoring the academic skill data of learners in order to classify their employability at the early stage of graduation. The second aspect consists of skill-set assessment based on clustering to improve their required skill set through e-learning. Finally, an adaptive resource usage elasticity prediction is made. Experimental results show that the proposed approach achieves 96.45% accuracy of classification.

By utilizing the information gathered by IoT devices to make smart decisions about the quality of education and the academic environment, Ahanger et al. [50] developed an intelligent framework based on a hybrid cloud/fog infrastructure for education quality assessment. They proposed a model based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) for decision modeling based on the education quality scale determined by classification at the fog layer. Results show the effectiveness and reliability of the model with good accuracy about the quality of education access compared to the most recent decision models.

The authors of [51] presented a particle swarm optimization (PSO)-driven edge computing method that might aid in the cooperation and optimization of various ideological and political course resources in a mobile edge computing 5G network for intelligent education assessment on ideology and politics. The authors define the optimization issue as reducing the worst-case energy consumption in task offloading, as well as the decision-making and resource allocation of task offloading supported by edge caching. The outcomes of the experiment show that the suggested method achieves a high level of experience and energy conservation.

5. Smart Industry

Edge computing and AI play an effective part in the automation of large-scale industrial processes by providing efficient distribution of applications and an intelligent deployment strategy that provides ideal service delivery to users and customers. For the intelligent industry, fast and real-time detection of machine malfunction and preservation of product quality are very important. In addition to providing high-quality commercial operations in the industrial sector, the management of products provides suitable actions to prevent wastage of the products and high service delivery, whereas in the field of the finance industry, by constructing a smart financial technology application, banks and financial institutions may provide quality services to their consumers via individualized virtual supervision [52].

5.1. Financial Industry (FI)

Manusami et al. developed in [52] designed a ranking-based strategy to classify financial tasks arriving at the edge according to their priority as risky and nonrisky tasks. So as to minimize network energy consumption, the ranked financial tasks are assigned to appropriate computing devices for further analysis by using a service-deployment mechanism based on a perfect matching theorem in graph theory. Subsequently, SVM is used to analyze the ranked tasks at the edge networks for immediate prediction and detection of fraud.

An early warning model for financial risk prediction of the enterprise based on mobile edge computing (MEC) is proposed in [53]. The authors used an optimized BPNN with an edge service preloading optimization model, which is applied based on the information obtained about the geographical information related to points of interest and BPNN. Then, according to the user’s location feature vector, the probability of the user’s next service is predicted. Results show that the service preloading optimization based on the geographic information points and BPNN improves the response speed.

5.2. Commercial Industries (CI)

In [54], Neelakantam et al. designed a fog computing framework for product demand forecasting and decision-making. They used PCA and K-means for clustering products based on product demand and grouped products into three categories, namely, low, medium, and high demand. Then, the reinforcement learning model is used for product distribution decision-making.

5.3. Machine Malfunction Monitoring (MMM)

The authors in [55] proposed a framework based on fog computing to analyze and classify the machine sounds in order to monitor and identify the malfunctioning machines. To extract the important features of the audio signal, the authors used linear prediction coefficients (LPC) and melfrequency cepstral coefficients (MFCC). Then, they used supervised machine learning models (such as RF, SVM, AdaBoost Classifier, and MLP) to detect and classify the malfunctioning machine sounds as normal and abnormal. These models showed their performance in detecting low-level sound from the audio signal and enhancing the service time.

Syafrudin et al. proposed in [56] an edge-based fault detection by using density-based spatial clustering for outlier detection and for covering the imbalanced data issue. The oversampling SMOTE method is used, whereby an RF algorithm is applied in prediction. The proposed method achieves higher accuracy and fast fault detection.

In [57], Fawwaz and Chung proposed an edge-cloud framework for real-time fault detection based on combined LSTM-AE algorithms. This handles both multivariate time series and noisy data. First, a novel correlation and redundancy-aware feature selection (CRFS) approach by a genetic algorithm is implemented. Then, a pre-trained model is conducted on the cloud with the combination of LTSM and AE. Secondly, the pre-trained model is transferred to the edge for real-time fault detection. Experimental results show the effectiveness of the model by achieving shorter detection times, better accuracy, and more robust performance in the presence of noisy data.

Park et al. [58] developed a model for real-time machine fault detection in smart manufacturing. A lightweight LSTM is developed for an edge device and a Raspberry Pi for implementation. Results show that the model outperforms the existing models.

Li et al. [59] designed collaborative fog-cloud computing for inspection manufacturing by using CNN with offloading strategies. These latter offload the low layer of CNN to the fog nodes. For fast detecting defects in a product and identifying its degree, an early exit strategy is used. The proposed method reduces the data transmitted to the cloud and hence can perform real-time detection.

5.4. Product quality monitoring and prediction (PQMP)

Feng et al. [60] proposed an edge-based assembly quality prediction in an industrial IoT environment. They used an RF for feature selection while the SMOTE–Adaboost method with jointly optimized hyperparameters was used for imbalanced classification. The experimental findings demonstrate that, in terms of predicting assembly quality, the suggested technique is more accurate than existing classification methods.

In [61], the authors proposed a fog-based framework for tool wear monitoring and prediction. First, the authors used both CNN and LSTM to extract tool wear temporal features on fog nodes. Then, a bidirectional LSTM model (BiLSTM) is performed on the cloud for tool wear prediction based on the features extracted by the MCLSTM model. Results show the effectiveness of the model in terms of high monitoring accuracy and low response latency.

For real-time and efficient processing tasks in smart production lines, Wang and Li [62] proposed a hybrid heuristic algorithm, an improved particle swarm optimization (IPSO) algorithm, and the improved ant colony optimization (IACO) for task scheduling in fog computing in order to solve the problem of end devices with low computational power and significant energy use.

6. Smart Healthcare

IoT, AI, and edge computing paradigms are considered major keys to the new revolution in healthcare by providing an intelligent system that aims at improving the quality of care services such as (i) remote physical patient monitoring, and (ii) automatic diagnosis and detection of diseases at early stages.

6.1. Diet Health Management (DHM)

One of the main reasons for health damage is an unhealthy diet. To tackle the automation of dietary assessment, authors in [63] proposed a food-recognition model with a deep residual convolutional neural network, which determines whether the food photos include enough vegetables. In order to make predictions on a mobile device without connecting to a cloud server, the authors quantized the network weights of the proposed model by using posttraining quantization methods into low-bit fixed-point representations.

Likewise, Liu et al. [64] proposed a DL-based food recognition for assessing diets. Taking into account the limited computation resources and low battery life on mobile devices, the preprocessing and segmentation of food images have been performed on edge devices (smartphones). At the same time, the classification with a pre-trained GoogLeNet model for feature extraction and softmax classifier was done on a cloud server. The model exceeds other works in terms of accuracy, with a quicker response time and reduced energy use, according to experimental results.

6.2. Ambient Assisted Living (AAL)

For accurate and timely fall detection, the authors of [65] developed an intelligent system based on fog/cloud computing architecture. The cloud data analysis resources are used to train the hybrid DL model (GRU/LSTM), whereas the DL model inference is implemented on a fog smart gateway for real-time fall detection and alert notification to caregivers' smartphones. To overcome the complex challenges of resource limitations on the fog for DL inference, an efficient and automatic deployment is performed by using virtualization technologies. Results show how well the system works for providing quick, precise responses and enhancing customer service.

For elderly patients with chronic disease monitoring, Hassan et al. proposed in [66] a fog/cloud framework. A firefly algorithm (FA) was used to optimize the NB classifier by selecting the minimal features that yield the highest accuracy. The framework collected data from the elderly patient by using ambient and biological sensors, fused the data into contextual states, and utilized context-aware algorithms to forecast the patient's health status in real-time.

The introduced framework includes a five-phase classification method to handle huge datasets that are unbalanced as a result of elderly patients being followed for an extended period of time.

In [67], the authors proposed a framework for real-time fall incident monitoring by using ML algorithms based on fog computing. First, they used linear discriminant analysis (LDA) to reduce the dimensionality of extracted features. Then, they employed SVM and KNN for classification.

Divya et al. [68] proposed a fall detection framework. It consists of four layers: edge devices, mist, fog, and cloud. The edge consists of a smart camera, which deploys a compressed DNN model for fall detection. Basic data filtering and rule-based decision-making are handled by the mist. Images are transmitted to the cloud storage only when a fall is detected, and the edge detection output is only delivered to the higher fog layer if a fall is observed. Xtreme gradient boosting and RF methods are used to build the model in the cloud.

The authors of [69] designed a cloud/edge-based federated learning framework for in-home health monitoring named FedHome. The authors used a lightweight convolutional generative autoencoder to deal with the unbalanced and non-ID distribution health monitoring data with high accuracy in predictions.

6.3. Human Activity Recognition (HAR)

The authors of [70] introduced a light DL framework that uses SMOTE to solve the problem of imbalance labels and implemented a CNN embedding feature (CNNEF) to understand abnormal human activities through the sensor data in edge nodes to predict the user’s behavior, detect anomalous activities, and offer more accurate, efficient, and real-time services. Then, the extracted high-level embedding features from CNNEF are given to the classical ML algorithms, such as logistic regression, KNN, DT, NB, RF, and SVM.

A brand-new DL-based human activity recognition framework for edge computing termed DL-HAR was suggested in [71]. The proposed framework seeks to accelerate decision-making. It employs a DL algorithm to cut down on communication with the cloud servers, cutting down on potential delays and round trips. In order to detect the activity time-series data coming from sensors or smartphone devices, the framework first trains the DRNN model on the server side because of its high capacity and then transmits the image of the learned DRNN model to Docker containers on Raspberry Pi3 edge devices.

In [72], the authors proposed an edge-based framework for human activity recognition designed for wearable edge devices. The authors design an energy-efficient solution by using an adaptive CNN that selects a portion of the baseline architecture to use during the inference phase instead of using the full architecture.

The authors of [73] proposed a blockchain based on a fog monitoring system to identify human activities as an interface of e-healthcare services. The proposed framework categorizes and classifies the video frames based on patient activities by using the SVM algorithm. Videos of various human activities are retrieved by using a multiclass cooperative categorization approach to increase the activity classification accuracy in video features, which are then processed into action vocabulary for efficiency and accuracy. In a similar manner, an SVM based on the error-correction output codes (ECOC) architecture is used to classify activities.

A Bayesian deep learning network, which aids in inferring and accurately identifying various physical data acquired from individuals to track their physical activities, was examined by the authors of [74] by utilizing edge computing. The effectiveness of this wearable Internet of things system with multimedia technology is then assessed by using the results of some experiments and analyzed in terms of accuracy, efficiency, mean residual error, delay, and energy consumption.

In order to anticipate health conditions in real-time based on an individual's physical postures, the authors of the paper in [75] developed a fog/cloud system. In this study, they use the continuous time series policy to store anticipated activity ratings on the cloud and give future health references to accredited medical professionals. The physical abnormality that is predicted and the level of health severity are closely correlated with the issuance of the warning. Clear benefits of fog analytics over cloud-based monitoring systems include an improvement in the recognition rate of up to 46.45% for 40 FPS and 45.72% for 30 FPS. By attaining high activity prediction accuracy and low latency, the computed results demonstrate why the proposed fog analytics monitoring system is preferable to other cloud-based monitoring solutions.

6.4. Location-Based Disease Prediction (LDP)

Ahanger et al. developed in [76] a fog/cloud framework to forecast COVID-19 cases, employ user-held devices, and track the disease's spread. First, to identify contaminated individuals and areas, the authors used fuzzy C-mean classification. Then, in order to predict the possibility of COVID-19 symptoms in the geographical patterns, the authors used a temporal recurrent neural network. The self-organization mapping (SOM) method is used to present data on geolocations for COVID-19 dynamical behavior over spatial–temporal domains.

The authors of [77] proposed a fog-cloud framework for remote diagnosis of ENCPH spread based on the patient's health symptoms and the surrounding environment. The fog layer analyzes a patient's category based on parameters from health-related data by using a fuzzy C-Means classifier. At the same time, the prediction model based on spatiotemporal domains that use T-RNN is used to manage medical resources. A SOM technique is used for outbreak geographic visualization.

A novel fog computing-based e-Healthcare framework was presented by Majumdar et al. in [78] to monitor KFD-infected patients throughout the early stages of infection and manage the disease epidemic. A new extremal optimization-tailored neural network classification technique has been created by employing the hybridization of the extremal optimization with the feed-forward neural network in order to guarantee a high prediction rate. A location-based alert system has also been recommended to give each KFD-infected user's location information based on their GPS location as well as the locations of risky areas as soon as possible in order to prevent the epidemic.

A fog-assisted cloud-supported healthcare system was created by Vijayakumar et al. in [79] for the real-time identification and prevention of illnesses spread by mosquitoes. The categorization of illnesses spread by mosquitoes has been done based on symptoms. The registered user is divided into infected and uninfected groups by using a fuzzy KNN algorithm. Social network data is examined to identify risky regions. Alert messages have been sent to registered users in an attempt to avoid an epidemic so they may stay away from risky locations.

The authors of [80] designed an edge-cloud collaborative learning framework for the local diagnosis of COVID-19 by using the VGG16 algorithm. The authors used a clustering federated learning approach in order to solve the heterogeneity and the divergence in the data distribution.

Singh et al. developed in [81] a fog-based quality of service (QoS) framework to monitor the state of health of citizens and prevent and ensure safety from COVID-19. The fog layer provides real-time processing of users' health data in order to predict COVID-19 infection. The unique patient identification, which is made up of patient data and geographical information, is then transferred to the cloud layer for further processing when the diagnosis is positive. The results of the experiments show that the proposed model is very efficient for remote diagnosis of COVID-19 infection and may be utilized as a time-saving substitute for labor-intensive clinical diagnostic procedures.

Singh et al. developed in [82] a collaborative edge/cloud framework for remotely diagnosing COVID-19. For the purpose of easy deployment on low-powered mobile devices and devices and quick diagnosis, they used an optimized DL model inspired by the MobileNet V2 model architecture. The model was first trained on the cloud; then its backup was sent to edge devices to perform the diagnosis of COVID-19 infection. Finally, when the diagnosis is positive, the unique patient identifier composed of patient information and location information is sent to the cloud layer for further action. Experimental results demonstrate that the proposed model is very effective for remote diagnosis of COVID-19 infection and can be used as an efficient alternative to time-consuming clinical diagnostic tests.

In [83], the authors proposed an intelligent health monitoring framework, iCovidCare for the prediction of coronavirus disease based on an ensemble RF model. First, a rule-based approach is employed at the local device to diagnose the coronavirus disease based on the temperature sensor data. Then at the cloud server, the feature selection, and fusion are applied for COVID-19 disease prediction.

6.5. Disease Diagnosis (DD)

In order to achieve an early and accurate diagnosis and detection of lung cancer while maintaining privacy, low latency, and mobility, Prabukumar et al. developed in [84] a fog-based system for the diagnosis of lung nodules. First, fuzzy hybrid C-Means and region-growth segmentation algorithms were used for image segmentation and feature extraction. Then, cuckoo search and SVM were used for feature selection and classification, respectively.

A paradigm for intelligent patient monitoring of cardiomyopathy patients by using sensors and wearable technology is presented by the authors in [85]. By relocating sensors in the monitored region, a fuzzy Harris hawks optimizer (FHHO) is first utilized to expand the coverage of monitored patients, and then a wearable sensing data optimization (WSDO) algorithm is employed for heart rate detection. The experimental findings show that the optimized model is successful in terms of the number of sensors used, accuracy, and response time, as well as sufficient patient coverage.

A real-time smart remote monitoring system for patients with chronic illnesses was suggested by the authors in [86]. Four layers make up the suggested framework: the sensing layer for data collection, the edge device layer for offline preprocessing, the edge server layer, and the cloud layer for further online operations. For the purpose of forecasting the patient's health status in dispersed emergency occurrences, the offline classification techniques are trained in the cloud. The whale optimization algorithm (WOA) and NB are used in the suggested technique to choose a small collection of features with a high level of accuracy.

The authors of [87] proposed an ensemble approach based on data fusion in fog computing by using medical data from body sensor networks (BSNs) for heart disease prediction. For their classification technique, they included a number of temporal and frequency domain characteristics in a kernel RF ensemble. To create higher quality data that is input to the ensembles for heart disease prediction, data from many sensors is fused.

The authors of [88] proposed an adaptive neuro-fuzzy inference system model for Parkinson's disease prediction. The fog takes a prominent role in feature extraction from IoT sensors and provides the principal functions. Then, the model's parameters are adjusted through grey wolf optimization (GWO) and PSO. Results show that the proposed model successfully predicts Parkinson's disease with good accuracy.

Shynu et al. developed in [89] a fog computing-based framework for disease prediction. First, for the protection and effective data storage and data sharing, a blockchain in the fog nodes is used. The patient data for patients with diabetes and cardiovascular disease are then initially grouped by using a rule-based clustering method. Finally, a feature selection-based adaptive neuro-fuzzy inference system is used to predict diabetes and cardiovascular illnesses (FS-ANFIS).

In order to provide low-latency responses in identifying emergency situations for cardiac patients, Cheikhrouhou et al. proposed in [90] a remote cardiac patient monitoring based on hybrid fog-cloud architecture for analyzing ECG signals captured from IoT wearable devices. Results show that the proposed approach based on a one-dimensional CNN approach for arrhythmia cardiovascular disease detection could achieve an accuracy of 99% with a 25% improvement in the overall response time.

Similarly, for real-time physiological data analysis, the authors in [91] designed a framework for health monitoring based on fog computing. The system consists of three layers. The first is the wearable layer wherein an RK-PCA eliminates erroneous data. A fog layer, which consists of an onlooker node is used to eliminate redundant data generated by wearable devices and health status prediction. Then fog nodes for health status detection. Finally, there is a cloud layer for data storage. In addition, a multiobjective optimization algorithm is used to solve fog overloading in smart healthcare applications. Experimental results show the stability of the system compared to the cloud-based approach, while less latency, execution time, a high detection accuracy are improved.

In [92], the authors proposed a deep learning model to be supported by edge computing and investigated it in the diagnosis for identification of heart disease from the data collected by using IoMT devices. The proposed effective training scheme for DNN (ETS-DNN) model incorporates a modified hybrid water wave optimization technique to tune the parameters of the DNN structure.

To improve the detection of impending hypoglycemia, the authors of [93] developed an embedded deep-edge learning model by using evidential regression and attention-based recurrent neural network for real-time blood glucose.

7. Smart Transportation

The use of IoT and AI technologies in the transportation field consists of collecting information about vehicles, drivers, and roads with the objective of creating a real-time traffic management system by performing traffic road condition monitoring, detecting events in real time for traffic safety, and preventing perturbations that impact on traffic flow and parking availability.

7.1. Smart Parking Management (SPM)

The authors of [94] suggested an edge computing-based shared bicycle system, with a hybrid ML model (SOM-RT) and a self-organizing mapping network to assemble the original samples in the form of clusters, and each cluster was built as an RT to forecast the necessary number of bikes at each station. Experiments outperformed other methods in terms of prediction accuracy and generalization.

The authors of [95] developed a camera-based object-detection solution for parking surveillance. They used a single-shot multibox detector (SSD) and background-based detection method in pipeline at the edge to reduce the data transmission volume and ensure efficient updates, whereas the detection results are combined on the server to perform parking occupancy detection in extreme lighting conditions and occlusion conditions with a tracking algorithm for vehicle tracking in parking garages.

In [96], Huang et al. created the fedparking federated learning framework for the management of parked vehicle-assisted edge computing (PVEC). Fedparking uses federated learning with LSTM to estimate parking space. Fedparking enables many parking lot operators to jointly develop a model to forecast the availability of free parking spots in a parking lot in real time for traffic management. For PVEC, they utilized an incentive system. A multi-agent deep reinforcement learning strategy was utilized to progressively attain the Stackelberg equilibrium in a distributed yet privacy-preserving way while taking into account the dynamic vehicle arrivals and time-varying parking capacity limitations. High convergence accuracy is obtained by this method.

7.2. Traffic Monitoring/Prediction (TMP)

To solve the dynamic traffic changes issue in smart transportation for accurate traffic prediction and for identifying the abnormal situation in real-time, the authors of [97] proposed a model for collaborative optimization of intelligent transportation systems. Installing monitoring sites at various traffic crossings allows for data collection from each intersection. The DBN-SVR approach is used to anticipate traffic conditions and predict the overall traffic flow of the road network. Advanced computer technology was employed to process the information signals produced by the crossings after the model was used to determine the traffic flow of a few chosen intersections.

For accurate real-time traffic flow prediction, a framework named AAtt-DHSTNet based on fog computing is proposed in [98]. The authors used an aggregation method based on an attention mechanism to eliminate redundant data acquired by sensors in overlap regions, along with a spatial and temporal correlation-based DHSTNet model, which dynamically manages spatial and temporal correlations through CNN and LSTM models.

For real-time urban traffic prediction, a short-term traffic flow prediction model based on edge computing is introduced in [99]. The authors used a smooth support vector machine optimized by a chaotic particle swarm optimization algorithm.

The authors of [100] proposed a federated learning approach to predict the number of vehicles in an area. First, they used clustering to group participants. Then, they trained a global model for each cluster. They used a joint-announcement protocol in the model aggregation mechanism to reduce the communication overhead of the algorithm.

In [101], the authors proposed an edge computing-based graph representation learning approach for short and long-traffic flow prediction. The authors used a federated learning approach. Each model at the edge consists of three components: (1) recurrent long-term capture network (RLCN) module, (2) attentive mechanism federated network (AMFN) module, and (3) semantic capture network (SCN) module for spatiotemporal information in each area. The authors used an additive homomorphic encryption approach based on vertical federated learning (VFL) to share the model.

7.3. Intelligent Transportation Management (ITM)

In [102], the authors introduced a system based on edge/cloud computing for real-time driver distraction detection by using a custom DCNN model and a VGG16 (namely, visual geometry group-16)-based model.

A driving behavior evaluation technique built on a vehicle edge-cloud architecture is taken into account by Xu et al. in the work at [103]. When a car is operating on the road, its telematics box transmits data displaying the autopilot/driver behaviors to the edge networks. The driving behavior evaluation model built by the cloud server is used by the edge networks, which then communicate the behavior rankings back to the cars. The driving behavior evaluation model is continually trained and optimized on the cloud server by using vehicle data, and the model is periodically sent to the edge networks for updates. The suggested scheme’s robustness and feasibility are demonstrated by experimental findings.

A methodology for diagnosing railway faults based on edge and cloud collaboration is created in [104]. The model first uses a SAES-DNN for the fault recognition method on the cloud. Then, for a real-time fault diagnosis, a transfer learning strategy is used to assign the task on the edge.

8. Security and Privacy in Edge-Based Applications

With the recent exponential sophistication of attacks and unauthorized access and in order to ensure and improve the privacy and security of edge-based IoT applications, putting an AI-based solution at the edge of the network is necessary.

8.1. Privacy Preservation (PP)

Kumar et al. [105] suggested two techniques for privacy preservation: blockchain and deep learning implemented on the fog nodes in the Collaborative Intelligent Transportation System. The blockchain and the smart contract-based module are used at the first level to support the exchange of nonmutable data. The deep learning module LSTM-AE is used to encode the C-ITS data into a novel format to prevent attacks. Finally, an attention-based RNN is employed for attack detection.

Similarly, Kumar et al. [106] proposed an integrated safe privacy-preserving architecture for smart agricultural drones that integrates blockchain and DL methods. The framework uses two levels of privacy. A blockchain-based ePoW and smart contracts are included in the first level, and an SAE approach to transform data into a new encrypted format is included in the second level. It uses a stacked short-term memory (SLSTM) anomaly detection engine.

Authors in [107] proposed a model based on differential privacy, called differential privacy fuzzy convolution neural network framework (DP-FCNN). First, they used the addition of noise to protect sensitive information by using a fuzzy CNN with a Laplace mechanism, then secured data storage, and encryption with a lightweight encryption algorithm named PICCOLO before uploading it to the cloud.

To prevent the leakage of users' privacy-sensitive data, authors in [108] proposed a federated learning with a blockchain-based crowdsourcing framework. The authors used differential privacy to protect the privacy of customers' data. The model updates are accountable for preventing malicious customers or manufacturers from using the blockchain.

8.2. Authentication and Authorization (AA)

The authors of [109] presented a DL-based physical layer authentication strategy that takes advantage of channel state information to improve the security of MEC systems by spotting spoofing attacks in wireless networks. The DL-based multiuser authentication method put forward in this research can successfully distinguish between trustworthy edge nodes, malicious edge nodes, and attackers, greatly enhancing the security of MEC systems in the IoT.

In order to achieve high efficiency and the most effective use of computing resources, the study in [110] presents an effective implicit authentication system called edge computing-based mobile device implicit authentication (EDIA). The gait data from the built-in sensors are processed in an optimum manner, and the model is based on the concatenation of CNN and LSTM. By transforming the gait signal into an image, data preprocessing is utilized to extract the characteristics of the signal in a two-dimensional space. A hybrid approach using CNN and LSTM is used for user authentication, with CNN serving as a feature extractor and LSTM serving as a classifier. The authentication technique also achieves excellent authentication accuracy with modest datasets, demonstrating that the model is appropriate for mobile devices with limited battery and processing resources.

8.3. Intrusion Detection (ID)

Samy et al. proposed in [111] a distributed fog framework for IoT cyberattacks by using the LSTM model. First, with the aim of achieving the scalability of the system, a clustering-based mechanism is applied to the fog nodes to balance the network load and increase network scalability and secure the exchanged traffic between the fog and the cloud. The proposed framework has proven its effectiveness in terms of response time with a high detection accuracy compared to cloud-based attack detection systems.

In [112], authors proposed a fog-based framework for detecting attacks using a hybrid DL model CNN-LSTM with the use of centralized controller software-defined networking (SDN) to reduce computation overhead with a highly cost-effective dynamic.

In [113], an IDS is proposed based on the DL approach by using AE and isolation forest (IF) in a fog environment. After identifying the attack and separating it from data from regular network traffic, AE uses an isolation forest to find the outlier data points.

The authors of [114] proposed a lightweight algorithm for resource-constrained mobile devices for attack detection by using a stacked AE, mutual information (MI), and wrapper for feature extraction and SVM for the detection.

In [115], Huong et al. proposed an IoT platform that uses edge and cloud computing for attack detection based on multilayer classification and federated learning. A feature extraction-based PCA coupled with an optimized neural network is implemented for a low-complexity model and good accuracy. However, there is a limitation in the model, which consists of the imbalanced data distribution on fog nodes. This limitation decreases the accuracy of detection for some types of cyberattacks.

In [116], Gavel et al. designed a fog-based model for intrusion detection in an IoT network. The model is based on a combination of the Kalman filter and the salp swarm algorithm. First, the Kalman filter is used as a data fusion technique that reduces the redundant data at the fog node. Then, the salp swarm algorithm is used to select the optimum number of features. Finally, the features selected are used to train the model using the kELM classifier. Results achieve highly reduced data, and high detection accuracy with reduced computation time.

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