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The Healthcare Monitoring System Based on Artificial Intelligence Protocols

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Abstract*:* The need for high-quality healthcare is growing as the world's population rises. Modern technological developments enable a machine to check a patient's health from a distance just as well as if the patient were present in the hospital. This article examines a real-time Internet of Things (IoT)-based remote patient monitoring system designed to prevent a variety of health problems, including diabetes, strokes, etc. In order to immediately identify and prevent health issues, our study entails the real-time collecting of many vital metrics from patients utilizing linked devices. The data is then saved in a database and analyzed using artificial intelligence algorithms.

Keywords: *Internet of Things (IoT), connected devices, cloud computing, data analysis, artificial intelligence, machine learning, deep learning, algorithms, stroke (AVC), diabetes and healthcare.*

1. Introduction

The Internet of Things has expanded the possibilities of human interaction with the environment while enhancing freedom. In this hyper-connected world, digital systems can record, monitor, and adjust every interaction between connected objects [1], [2], [3]. Thanks to cost-effective computing, cloud technology, Big Data, artificial intelligence algorithms, and mobile technologies, smart objects can share and collect data with minimal human intervention.

The healthcare sector has recently experienced significant development. Just a few years ago, disease diagnosis required a physical examination at the hospital, and patients remained hospitalized while undergoing therapy, leading to increased healthcare expenses and burdening healthcare facilities. With technological advances, it is now possible to diagnose many diseases and monitor your health remotely using smart connected objects and thus find a suitable solution for the problem of medical deserts. Clinical parameters, can be measured remotely without the help of a health professional [1], [2], [3], the collected clinical data is sent from remote areas to data servers hosted in healthcare facilities through the Internet of Things. To collect physiological data from patients, such as temperature, heart rate and blood pressure electrocardiogram (ECG), electroencephalogram (EEG), etc., embedded or portable sensors are used in healthcare applications, other environmental data can also be captured, including temperature, oxygen level, time and date [4], [5], [6], in addition to data collected at distances.

These can be recorded from many sources: doctors, patients, x-rays, scans, and others who are authorized to access the data acquired by the detection devices. Access to and exploitation of collected clinical data has become increasingly rapid thanks to cloud computing applications, machine learning and big data analytics [4]. These data are used to develop accurate analyses and a relevant assessment of the patient's health. With client/server technology, healthcare professionals can diagnose patients and take the necessary medical measures, but the main challenge is to work on an IoT system that maintains a quality of service matrix, which takes into account the cost, the availability, prevention, reliability, and confidentiality of information [7]-[12].

In this article, we begin with an introduction followed by a paragraph that presents the protocols used for real-time collection of a set of vital parameters of connected object menu patients, then in the second paragraph, introducing us to the main protocols of AI used to improve the diagnosis and prediction of diseases, then in a third paragraph we will present the results and their interpretations, and finally we conclude with a conclusion and perspectives.

2. IoT solution architecture

In this work, we decided to collect and monitor physiological patient data, Figure 1, and summarize the architecture of the deployed IoT system [13]-[20].

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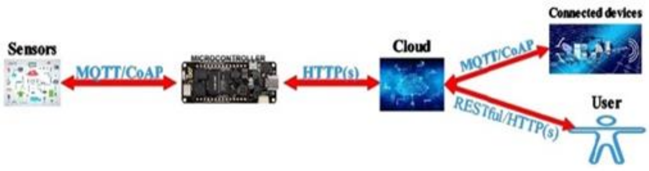

Fig. 1. Messaging protocols used with IoT devices.

The collected data is transferred and routed to our cloud in the form of certain secure messaging protocols [21]- [27], including:

- **HTTPS**: widely used for secure web communications.
- **MQTT/TLS (Message Queuing Telemetry Transport/ Transport Layer Security):** often used for its lightness, ease of implementation and support for pub/sub (publication/subscription). It also secures data transmission between the gateway and the cloud MQTT server.
- **CoAP (Constrained Application Protocol)**: is designed for resource-constrained devices and low-power networks.

At the end, the data is transferred to the final user via the mentioned protocols to visualize, analyze and interact with the collected data. This design approach makes it possible to efficiently, securely and reliably collect sensor data and then make it accessible to final users for different applications.

3. Modeling and integration of AI in healthcare

3.1. Related work

In order to help healthcare professionals at the early stage of diabetes and stroke diagnosis and with the aim of stopping the progression of these deadly diseases, recently, clinical trials have used machine learning technologies, data mining to predict the diagnosis of diabetes and stroke and the influence between them in patients. In this context, many articles have been carefully selected for an in-depth review, the articles [28]-[32] explore the application of artificial intelligence in the prediction of stroke and diabetes, The authors of these papers used machine learning techniques, such as deep neural networks and supervised learning algorithms, to develop models for predicting stroke and diabetes. The results of the study showed that artificial intelligence models were able to predict stroke in diabetics and with significant accuracy. Using the appropriate characteristics and optimizing the learning algorithms, the researchers obtained promising results [28-32]. These articles also highlight the challenges and potential limitations of using artificial intelligence in stroke prediction in diabetics, such as data availability, the quality of the data and the confidentiality of the medical information as well as the limit of use of some supervised learning algorithms with some cases of optimization [28]-[32].

3.2. Models and theory

Machine Learning (ML) plays an increasingly important role in the health sector, with the main objective of improving the diagnosis and prediction of diseases. In this paragraph, we present the methodological choices we have made to meet our scientific objective, which is to build a system of diagnostic aid and multiclass decision support to heterogeneous data. To begin with, we present the metrics adapted to a classification task, which is the confusion matrix and the associated kappa score [32]-[35].

3.2.1. The confusion matrix in machine learning

The confusion matrix is a tool that allows us to understand how "confused" or mistaken a machine learning model is. It is a table with the different actual cases listed in columns and the different predicted use cases listed in rows. In our case, for a medical test, the matrix would look like this [32]-[34]:

REEL
Whether the patient is affected or not

PREDICTED What our model predicted		Affected	Not affected
	Affected	Number of **True Positives**	Number of **False Positives**
	Not affected	Number of **False Negatives**	Number of **True Negatives**

Fig. 2. The confusion matrix in machine learning dataset.

So, we obtain the following values:

- **True Positive (TP)**: The actual and predicted values are identical and positive. The patient is sick, and the model predicts it.
- **True Negative (TN)**: The actual and predicted values are identical and negative. The patient is not sick, and the model predicts that they are not.
- **False Positive (FP)**: The actual and predicted values are different. The patient is not sick, but the model predicts that they are.
- **False Negative (FN)**: The actual and predicted values are different. The patient is sick, but the model predicts that they are not.
- **Accuracy**: It is the number of true positives (TP) divided by the total predicted positives (TP + FP).
- **Recall or Sensitivity**: It is the number of true positives (TP) divided by the total actual positives (TP + FN).
- **f1_score**: It is defined as the harmonic mean of accuracy and recall:

$$\text{f1}-\text{score} = \frac{2*(\text{Accuracy}*\text{Recall})}{Accuracy+Recall} = \frac{2\text{TP}}{2TP+FP+FN} \tag{1}$$

- **The ROC_AUC curve (Receiver Operating Characteristic Area Under the Curve)**: It is a graph showing the performance of a classification model at all classification thresholds across the entire two-dimensional area based on both precision and recall indicators.

In the articles cited in paragraph 2.1, the exploratory data analysis of the two datasets used (diabetes and healthcare) revealed a strong asymmetry in the distribution of classes. To solve this problem, we introduced a random under sampling technique in machine learning, particularly in the following classification algorithms: Logistic Regression (LR), Artificial Neural Networks (ANN), Decision Tree classifier (DT), AdaBoost, Random Forest (RF), SVM, Naïve Bayes (NB), XGBoost classifier, KNeighbors (KNN) classifier, and Gradient Boost [35]-[38].

3.2.2. Used datasets and data representation

Considerable efforts have been made to identify articles using machine learning and data mining research techniques applied to diabetes and cardiovascular diseases. Two databases were consulted. The dataset used in this analysis is from Kaggle's Stroke Prediction dataset. A brief explanation of the relationship between each variable and stroke is presented in Table 1 below. Our research focuses on public datasets. The raw dataset comprises 11,705 observations and 12 variables (of which 10 are independent and one is the target variable). The output variable of the dataset is "stroke," with a value of either 0 (indicating no risk of stroke) or 1 (indicating a risk of stroke being identified) [39]-[43]. And we have in Table 2 above a 9-column dataset that concerns diabetes. 8 of the 9 columns are our feature columns, while the last column (Outcome) represents our target column. Furthermore, all our columns appear to be composed of numerical data [44]:

To analyze the two datasets Diabetes and Healthcare and consequently identify the models that can indicate the presence of cardiovascular diseases, and diabetes, we applied cross-validation for each algorithm cited above to optimize the following four parameters: accuracy, recall, f1_score and ROC_AUC curve. To summarize the process, the data set is divided into k folds, then the model is trained and validated k times, at each iteration, k-1 folds are used for model training, and the remaining fold is used as a validation set to assess model performance. This process is repeated so that each fold is used exactly once as a validation set. Finally, the performance results on k iterations are aggregated to provide the desired performance. To improve the classifier's accuracy, we use the GridSearchCV method from scikit-learn for each model. This method is a tool for hyperparameter optimization, performing an exhaustive search over a specified parameter grid and evaluating Combinations through cross-validation. It aims to performance of the model, after the search, it remakes the model with the best parameters on the entire dataset [32]-[38].

Table 1. Description of the healthcare dataset.

Number	*Attribute*	*Value*	*Description*
1	Id	Numeric Value	Unique Identifier.
2	Gender	"Male", "Female" or "Other"	Genre du patient.
3	Age	Numeric Value	Patient's Gender.
4	Hypertension	"0" or "1"	Patient's Hypertension.
5	heart_disease	"0" or "1"	Cardiopathy.
6	ever_married	"No" or "Yes"	Marital Status of the Patient.
7	work_type	"children", "Govt_jov", "Never_worked", "Private" or "Self-employed"	Type of Employment.
8	Residence_type	"Rural" or "Urban"	Type of Residence.
9	avg_glucose_level	Numeric Value	Average Blood Glucose Level.
10	Bmi	Numeric Value	Body Mass Index (BMI).
11	smoking_status	"formerly smoked", "never smoked", "smokes" or "Unknown"	Patient's Smoking Status.
12	Stroke	"0" or "1"	Stroke.

Table 2. Description of the diabetes dataset.

Number	*Attribute*	*Value*	*Description*
1	Pregnancies	Numeric Value	Pregnancy Status.
2	Glucose	Numeric Value	Simple Monosaccharide.
3	BloodPressure	Numeric Value	Blood pressure is the force of blood pushing against the walls of your arteries.
4	SkinThickness	Numeric Value	The measurement of skin thickness in 66 patients with type 1 diabetes aged 24 to 38 years, followed by investigating whether it was correlated with long-term glycemic control and the presence of certain diseases.
5	Insulin	Numeric Value	A polypeptide hormone that regulates carbohydrate metabolism.
6	Bmi	Numeric Value	Body Mass Index (BMI).
7	DiabetesPedigreeFunction	Numeric Value	Function that evaluates the probability of diabetes based on family history.
8	Age	Numeric Value	Patient's Age.
9	Outcome	"0" or "1"	Class Variable (0 if non-diabetic, 1 if diabetic).

3.2.3. Method and Followed Algorithms

To achieve efficient classification on our two separate datasets by using a range of various algorithms and optimizing performance according to F1_score, accuracy, recall and ROC_AUC metrics, we followed the following logic: first, we started by cleaning and preparing datasets: processing of missing values, encoding of categorical variables, and standardization of numerical data. Second, we divided dataset into a learning and testing set to reliably evaluate model performance. Third, the selection of the ten algorithms mentioned below. Fourth, for each algorithm and each dataset, we trained our model using the training set and applied hyperparameter tuning through cross-validation (Grid Search and Random Search) for each model to optimize its performance according to the four targeted metrics below. Fifth is the evaluation of each model on the test set, calculating the F1_score, accuracy, recall, and ROC_AUC to objectively compare their performance. Sixth, adjusting and refining the models based on the results obtained, considering advanced techniques to further improve performance [32]-[38].

4. Results

4.1. Healthcare dataset

We first evaluated our algorithm on the healthcare dataset using ten classification models in a resampling procedure aiming to optimize the F1 score. The results were obtained and graphically represented. Figure 3 shows the F1 score values of the classification models applied to the Healthcare dataset. It appears that the XGBoost model, with an F1 score of 21.50%, stands out as the most effective in correctly predicting classes 0 (negative) and 1 (positive).

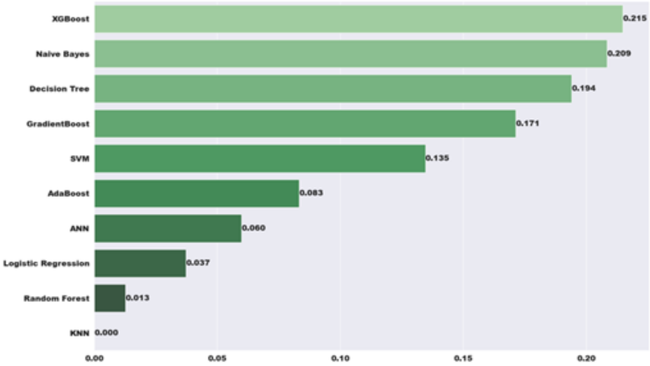

Fig. 3. Result of the F1 score of classification models applied to the healthcare dataset.

Figure 4 illustrates the performance of the ten classification models on the healthcare dataset, after an implementation of our approach focused on the optimization of the Recall score, the XGBoost model proved to be the most efficient, with an accuracy of 17,20% in the distinction between classes 0 (negative) and 1 (positive).

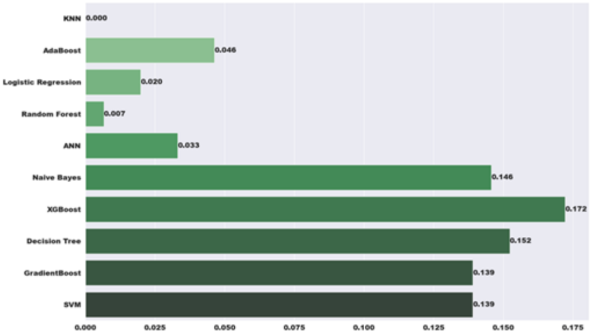

Fig. 4. Result of the Recall score of classification models applied to the healthcare dataset.

In addition, we examined the performance of the algorithm to improve the accuracy score by a resampling technique, we obtained results presented in Figure 5, these results show that KNN and AdaBoost are the most accurate models with a rate of 93.20%, specifically to identify classes 0 (negative) and 1 (positive) in the healthcare dataset.

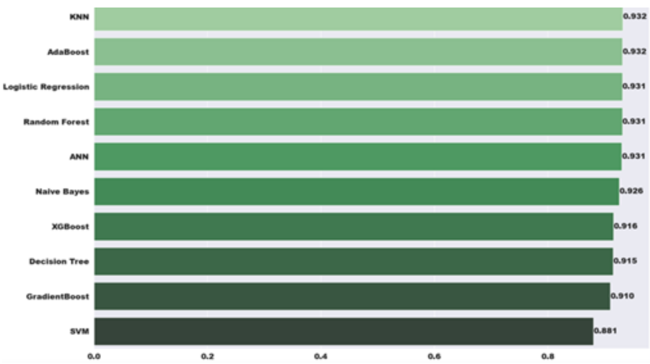

Fig. 5. Result of the Accuracy score of classification models applied to the healthcare dataset.

Figure 6 represents the variation of the ROC_AUC score of the ten classification models. According to Figure 6, we note that XGBoost is the best model showing an accuracy of 57.10% to predict classes 0 (negative) and 1 (positive).

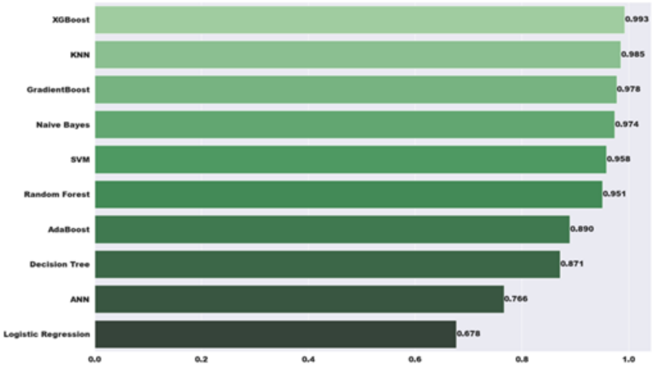

Fig. 6. Result of the curve ROC_AUC of classification models applied to the healthcare dataset.

4.2. Diabetes dataset

We then examined the performance of our algorithm on the Diabetes dataset. Figure 7, represents the F1 score variation, among the ten models, we note that, XGBoost achieved a peak performance with an accuracy of 99.30% for the prediction of classes 0 (negative) and 1 (positive).

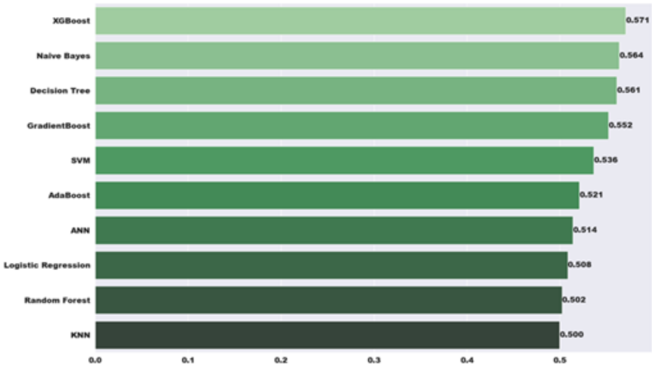

Fig. 7. Result of the F1 score of classification models applied to the diabetes dataset.

Figure 8, reveals that XGBoost outperforms other models by achieving 99.30% accuracy in prediction of binary classes 0 (negative) and 1 (positive).

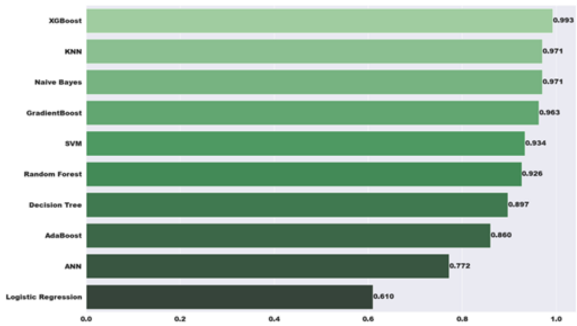

Fig. 8. Result of the Recall score of classification models applied to the diabetes dataset.

In order to improve the Accuracy score, we applied our algorithm on the dataset of the Diabetes dataset. Figure 9, shows the variation of Accuracy score, the model that stood out is XGBoost, with an accuracy of 99,50%, which testifies to its effectiveness in predicting classes 0 (negative) and 1 (positive).

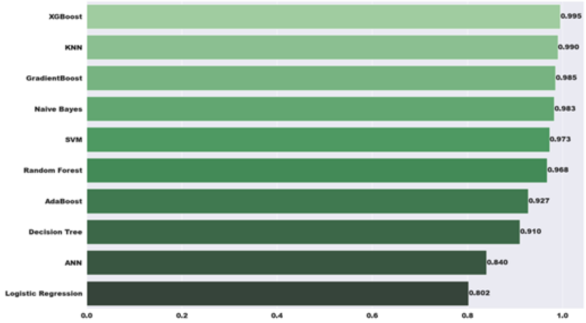

Fig. 9. Result of the Accuracy score of classification models applied to the diabetes dataset.

Figure 10 shows the variation of the ROC_AUC curve of the classification models after applying our algorithm to the ten classification models on the Diabetes dataset for a resampling procedure. According to Figure 10, it is observed that XGBoost is the best model with a value of 99.40%, indicating that the model is accurate to 99.40% in predicting the existence of both classes 0 (negative) and 1 (positive).

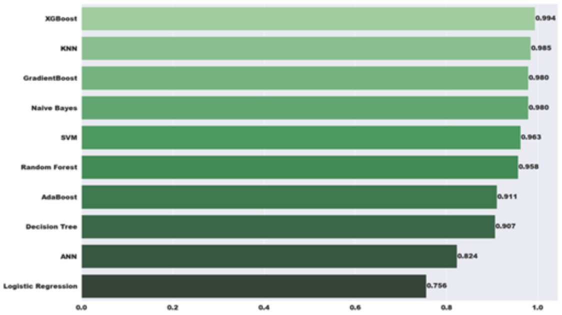

Fig. 10. Result of the curve ROC_AUC of classification models applied to the diabetes dataset.

To better conclude, we visually examined the results of all models in order to remove the best algorithm for each dataset questioned, we also used evaluations to analyze the effectiveness of nine classification algorithms plus the deep learning algorithm, to assess their influence on processing time and by checking all previous scores such as F1_SCORE, accuracy (Accuracy), Recall, and the ROC_AUC curve.

For both datasets, XGBoost and KNN using the accuracy score are the best models for future predictions on diabetic patients, while KNN and Adaboost using the accuracy score are the best for future predictions on stroke patients.

5. Conclusion

In conclusion, this article addresses the globally important issues related to the early non-invasive detection of stroke and diabetes, as well as the relationship between these two diseases. Specifically, our approach involves anticipating a classification problem in a dataset concerning strokes and diabetes. We used various models to classify predictions related to strokes and diabetes to achieve our goal, which is determining a person's propensity to have a stroke or to be diabetic and the relationship between the two. The results of this study suggest that the proposed AI algorithm is a reliable and reproducible tool to detect and quantify different biomarkers studied in this paper associated with various medical conditions, such as cardiovascular diseases and diabetic diseases which are currently considered prognostic even for treatment outcomes, thus offering promising prospects for improved medical diagnosis, understanding of pathophysiological mechanisms and the development of targeted diseases [39]-[42].

AI can facilitate the quantification of these biomarkers in daily practice since it has proven to be as accurate and precise as clinical evaluation, but takes less time. Further studies are needed to implement AI in large real-world contexts to assess changes over time and the clinical relationship between these changes and disease progression [43]-[45].

In addition, this technology could open up new research opportunities by identifying new biomarkers associated with complex conditions, contributing to a better understanding of diseases and the discovery of new treatments such as neurological disorders, cancers, metabolic diseases, autoimmune diseases, and many others [46], [47].

References

[1] Nishith Pathak; Anurag Bhandari « IoT, AI, and Blockchain for .NET», 2018.

[2] Kostas Siozios; Dimitrios Anagnostos; Dimitrios Soudris; Elias Kosmatopoulos « IoT for Smart Grids Design Challenges and Paradigms», 2019.

[3] Salman K. Salman « Introduction to the Smart Grid Concepts, Technologies and Evolution », 2017.

[4] Peter Waher; Pradeeka Seneviratne; Brian Russell «IoT: Building Arduino-Based Projects», 2016.

[5] Maciej Kranz, «Building the Internet of Things: Implement New Business Models, Disrupt Competitors, Transform Your Industry», 2016.

[6] Arshdeep Bahga; Vijay Madisetti, «Internet of Things: A Hands-On Approach», 2014.

[7] Sergey Balandin, Sergey Andreev and Yevgeni Koucheryavy, « Internet of Things, Smart Spaces, and Next Generation Networks and Systems », 2015.

[8] Kai Hwang and Min Chen, « Big-Data Analytics for Cloud, IoT and Cognitive Computing », 2017.

[9] Franco Cicirelli, Antonio Guerrieri, Carlo Mastroianni, Giandomenico Spezzano and Andrea Vinci « The Internet of Things for Smart Urban Ecosystems », 2019.

[10] E. Bruce Goldstein, «Cognitive Psychology: Connecting Mind, Research, and Everyday Experience», 2010.

[11] Ray Kurzweil,«How to Create a Mind: The Secret of Human Thought Revealed», 2014.

[12] Daniel Kahneman « Thinking, Fast and Slow», 2013.

[13] Keith Frankish; William Ramsey, «The Cambridge Handbook of Cognitive Science», 2012.

[14] Mark F. Bear; Barry W. Connors; Michael A. Paradiso, « Neuroscience: Exploring the Brain», 2015.

[15] Cai, Z.; Zheng, X.; Wang, J. Efficient Data Trading for Stable and Privacy Preserving Histograms in Internet of Things. In Proceedings of the 2021 IEEE International Performance, Computing, and Communications Conference (IPCCC), Austin, TX, USA, 11–13 November 2021; pp. 1–10.

[16] Aazam, M.; Zikria, Y. B.; Huh, E. N., « (Internet of things (IoT) in cloud computing environments: A survey. Computer Networks», p.103; P.39-52, 2016.

[17] Shan, «IoT and big data: The power to transform business models. CreateSpace Independent Publishing Platform», 2015.

[18] Zikopoulos; Eaton, «Understanding big data: Analytics for enterprise class Hadoop and streaming data. McGraw-Hill Education», 2014.

[19] Ponnusamy, V.K.; Kasinathan, P.; Madurai Elavarasan, R.; Ramanathan, V.; Anandan, R.K.; Subramaniam, U.; Ghosh, A.; Hossain, «E. A Comprehensive Review on Sustainable Aspects of Big Data Analytics for the Smart Grid. Sustainability», 2021.

[20] Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

[21] Kenneth C. Budka, Jayant G. Deshpande and Marina Thottan « Communication Networks for Smart Grids », 2014.

[22] Simone Cirani, Gianluigi Ferrari, Marco Picone and Luca Veltri « Internet of Things Architectures, Protocols and Standards », 2019.

[23] Domingos, P. (2015). The master algorithm: How the quest for the ultimate learning machine will remake our world. Basic Books.

[24] Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company.

[25] Gartner. (2021). Top 10 Strategic Technology Trends for 2021.

[26] Lee, K. M. (2018). Artificial intelligence and its impact on human society. Issues in Information Systems, 19(2), 34-41.

[27] World Economic Forum. (2018). The Future of Jobs Report.

[28] M. Sheetal Singh, Prakash Choudhary Stroke prediction using artificial intelligence 2017.

[29] Kim Mouridsen, Patrick Thurner and Greg Zaharchuk « Artificial Intelligence Applications in Stroke » 2020.

[30] R. Pitchai, Bhasker Dappuri, P. V. Pramila, M. Vidhyalakshmi, S. Shanthi, Wadi B. Alonazi, Khalid M. A. Almutairi, R. S. Sundaram, and Ibsa Beyene « An Artificial Intelligence-Based Bio-Medical Stroke Prediction and Analytical System Using a Machine Learning Approach » 2022.

[31] by Yan Liu, Bo Yin and Yanping Cong « The Probability of Ischaemic Stroke Prediction with a Multi-Neural-Network Model » 2020.

[32] Anna K Bonkhoffn and Christian Grefkes « Precision medicine in stroke: towards personalized outcome predictions using artificial intelligence » 2022.

[33] Dimitrios Serpanos and Marilyn Wolf « Internet-of-Things (IoT) Systems Architectures, Algorithms, Methodologies », 2018.

[34] B.K. Tripathy and J. Anuradha « INTERNET OF THINGS (IoT) Technologies, Applications, Challenges, and Solutions », 2018.

[35] Alessandro Bassi, Martin Bauer, Martin Fiedler, Thorsten Kramp, Rob van Kranenburg, Sebastian Lange and Stefan Meissner « Enabling Things to Talk », 2013.

[36] Site lora alliance.

[37] Site Bluetooth.

[38] Site Mircosoft Azure.

[39] Site of Organisation Mondiale de la Santé.

[40] Site of Organisation Panaméricaine de la Santé, Organisation Mondiale de la Santé.

[41] Simon NR, Frishman WH: Diabetes mellitus in the aging: Epidemiologic and therapeutic considerations. Am J Geriatr Cardiol Sep-Oct:22-36, 1992.

[42] Harris MI: Epidemiology of diabetes mellitus among the elderly in the United States. Clinics in Geriatric Medicine 6:703-19, 1990.

[43] Site Kaggle, dataset healthcare.

[44] Site Kaggle, dataset diabetes.

[45] Hatcher, W.G.; Qian, C.; Gao, W.; Liang, F.; Hua, K.; Yu, W. Towards Efficient and Intelligent Internet of Things Search Engine.IEEE Access 2021, 9, 15778–15795.

[46] Liang, F.; Qian, C.; Hatcher, W.G.; Yu, W. Search Engine for the Internet of Things: Lessons from Web Search, Vision, and Opportunities. IEEE Access 2019, 7, 104673–104691.

[47] Pan, S.J.; Yang, Q. A Survey on Transfer Learning. IEEE Trans. Knowl. Data Eng. 2010, 22, 1345–1359.