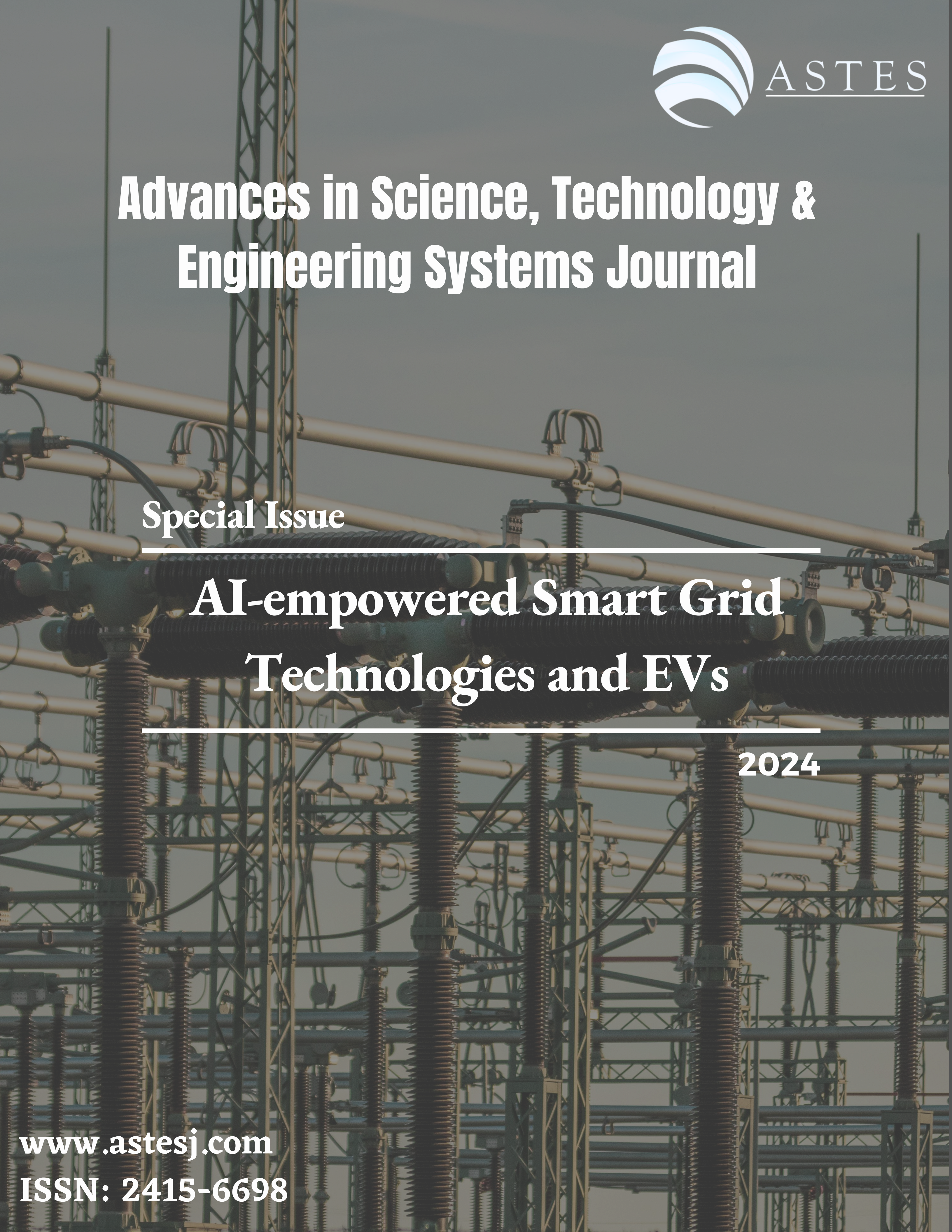

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Special Issue

AI-empowered Smart Grid Technologies and EVs

2024

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Editorial

The Special Issue on AI-Empowered Smart Grid Technologies and Electric Vehicles (2024) in the *Advances in Science, Technology and Engineering Systems Journal (ASTES Journal)* highlights a critical intersection of artificial intelligence, energy systems, and sustainable transportation. As global energy demands intensify and the transition toward low-carbon economies accelerates, the integration of intelligent technologies into power systems and mobility solutions has become increasingly essential. This issue brings together a collection of research contributions that explore how AI-driven innovations are transforming smart grids and electric vehicle ecosystems, enabling more efficient, resilient, and adaptive energy infrastructures.

A central focus of this issue is the application of artificial intelligence and machine learning techniques in optimizing smart grid operations. Several contributions examine predictive analytics for load forecasting, fault detection, demand-side management, and energy distribution optimization. These approaches enhance grid reliability and operational efficiency by enabling real-time monitoring and intelligent decision-making. The incorporation of AI into grid management systems also facilitates the integration of renewable energy sources, addressing challenges related to intermittency and variability while supporting a more sustainable energy mix.

Equally significant is the exploration of electric vehicle (EV) technologies and their interaction with modern power systems. The papers in this issue investigate advancements in battery technologies, charging infrastructure, and energy management strategies that support the widespread adoption of EVs. Particular attention is given to vehicle-to-grid (V2G) integration, where EVs function not only as transportation assets but also as distributed energy resources capable of supporting grid stability. This bidirectional relationship between EVs and smart grids represents a key innovation in the evolution of energy ecosystems.

The convergence of smart grid technologies and EV systems is further enriched by multidisciplinary approaches that combine electrical engineering, computer science, data analytics, and environmental science. Contributions highlight the role of IoT-enabled devices, cyber-physical systems, and intelligent communication networks in creating interconnected and responsive energy environments. These integrated systems enable enhanced coordination between energy generation, storage, and consumption, contributing to improved system resilience and sustainability.

Methodologically, the studies featured in this issue employ a diverse array of approaches, including computational modeling, simulation-based analysis, experimental validation, and real-world case studies. This diversity ensures both the rigor and applicability of the research, with many contributions offering scalable and adaptable solutions for modern energy and transportation systems. The emphasis on data-driven and AI-enabled frameworks reflects the ongoing shift toward intelligent and autonomous energy management.

The 2024 context provides a backdrop of accelerating electrification, digitalization, and environmental awareness. As governments and industries worldwide invest in renewable energy and sustainable mobility, the innovations presented in this issue align with broader efforts to reduce carbon emissions and enhance energy efficiency. The research underscores the importance of integrating advanced technologies to support the transition toward smarter and greener infrastructures.

The editorial team extends its sincere appreciation to the authors for their valuable contributions and to the reviewers for their insightful and constructive evaluations. Their collective efforts have ensured the quality and relevance of this special issue, reinforcing the journal's commitment to advancing interdisciplinary research in emerging technological domains.

This special issue offers a comprehensive exploration of how artificial intelligence is reshaping smart grid technologies and electric vehicle systems. By bringing together diverse perspectives and forward-looking research, it provides a meaningful foundation for continued innovation and collaboration in building sustainable, intelligent, and resilient energy ecosystems.

Guest Editor

Dr. Aparna Kumari

ADVANCES IN SCIENCE, TECHNOLOGY AND ENGINEERING SYSTEMS JOURNAL

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Impact of Integrating Chatbots into Digital Universities Platforms on the Interactions between the Learner and the Educational Content

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ABSTRACT

The rapid expansion of digital universities across Africa addresses the need for scalable higher education solutions, but challenges such as limited physical infrastructure and high dropout rates persist. In digital learning environments, effective interaction with educational content is crucial for student success. This article explores the transformative role of chatbots integrated into digital university platforms, with a specific focus on their impact on learner-content interactions. Leveraging the frequent use of messaging applications and advances in Artificial Intelligence (AI), we examine how chatbot integration enhances student engagement, facilitates personalized access to core educational modules, and supports formative assessments to reinforce learning outcomes. Using the Rasa open-source framework and the Moodle Learning Management System (LMS), we present a model that not only delivers content efficiently but also provides an interactive learning experience through AI-driven dialogue systems. Furthermore, a comparison of the different AI tools used for educational chatbots will be presented, to determine the most suitable solutions for digital teaching. This analysis will consider various aspects such as efficiency, customization, flexibility and ease of integration of the tools into educational environments. This study highlights how chatbots can foster a more dynamic and responsive learning ecosystem, ultimately improving student retention and mastery of key concepts in digital universities. In this article, we explore the broader impact of chatbots on learner interaction with educational content, not just their integration. It also emphasizes student engagement and retention.

1. Introduction

In recent years, digital universities have emerged across several African countries as a response to the growing demand for higher education. To address the challenges of massification and limited physical infrastructure, various digital universities [1], [2], [3] have introduced innovative pedagogical models, often relying on open digital spaces (ODS) to complement virtual environments. These ODS provide students with collaborative spaces to address pedagogical, technical, administrative, and social issues [4].

Students in digital universities primarily rely on distance learning platforms to access their educational materials. However, challenges related to the user experience and accessibility of certain Learning Management Systems (LMS) have contributed to increased dropout rates. To address these issues and improve access to educational content, universities have implemented various solutions, such as integrating social media and providing pedagogical support through tutors.

To further enhance the interaction between students and educational content, this paper proposes the integration of a chatbot into digital university platforms. By offering an intuitive and responsive interface, the chatbot aims to streamline content access and improve the overall learning experience. A chatbot is an advanced tool for automated, context-aware communication

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between users and systems, utilizing natural language processing for a conversational approach [5].

The remainder of this article is structured as follows: first, we will examine the related work in this area, followed by an overview of fundamental chatbot concepts. Next, we will discuss the design and implementation of our proposed solution, concluding with insights for future development.

2. The State of the Art

Artificial intelligence has left no stone unturned. Several researchers specializing in the field have carried out studies on the impact of AI in the education sector, and in digital universities.

Such is the case of authors of [5] who, in their article, propose the integration of conversational chatbots for educational remediation within the framework of covid-19. Among other things, the chatbot enables learners to self-train on parts of the course they haven't quite mastered.

It is connected to a Moodle platform, enabling learners to continue their learning at a distance. The chatbot is integrated as a Moodle plugin and can be used on other LMSs.

Researchers in [6], who propose and describe a new recommendation approach based primarily on the use of a chatbot linked to the Moodle platform.

The authors in [7], have proposed an intelligent agent in the form of a chatbot on the IBM Bluemix platform. This agent automates interaction between users and the Moodle training platform. This is a very interesting proposal, but it is specific to a technology belonging to IBM.

In [8], the authors set up a chatbot for a mobile application enabling interaction between users and a Moodle LMS platform. This tool is used on a specific LINE Chat application and meets a need of the Japanese community.

In [9], the authors have proposed a methodology to improve the quality of e-learning, chatbot architectural design, to help learners self-regulate their learning by accompanying them via a chatbot within the Moodle platform, which constitutes a metacognitive virtual assistant.

In [10], the authors with their chatbot in place, have enabled their institution's administration to reduce the amount of work they have to do to provide the required information to students, thus reducing their workload by continuing to answer all student questions. They also confirm that chatbot systems can be used in a wide range of sectors, including education, healthcare and marketing.

In [11] the authors conducted a comprehensive survey of recent deep learning techniques for chatbots, enhancing developers' understanding of effective chatbot design. In [12], the authors illustrates the design and development of illustrate at bot software, which integrates with a user website to manage student queries through defined intents. The article discusses the chatbot system utilizing a Recurrent Neural Network (RNN) for language processing, a Convolutional Neural Network (CNN) for image handling, and Dialogflow for intention and entity representation, along with keyword matching techniques. In [13], the authors have created three chatbots to support teaching in their university's Department of Electronics and Multimedia Telecommunications. The first, KEMTbot, is available on the department's website, providing information from the web and about the staff. The second chatbot assists students during exercises in the "Databases" course, while the third is an Amazon Alexa skill that responds to questions regarding the department on Amazon Echo devices.

3. Presentation of Artificial Intelligence (AI) tools used for educational chatbots

Natural language understanding (NLU) platforms are at the core of all chatbots. Conducting a comparative analysis of tools like Rasa, IBM Watson, Dialogflow, and TensorFlow is crucial to assess their strengths, weaknesses, and suitability for educational platforms such as Moodle.

3.1. Rasa

Rasa [14] is an open-source software that includes two main modules: Rasa NLU and Rasa Core. Rasa NLU focuses on natural language understanding, while Rasa Core handles dialogue management. The goal, according to its creators, is to bridge the gap between research and real-world applications, bringing recent advancements in machine learning to a wider audience, including those with limited experience who want to develop conversational agents.

3.2. Dialogflow

Dialogflow [15] is a natural language processing (NLP) platform developed by Google that enables the creation of chatbots and virtual assistants capable of understanding and responding to user interactions in natural language.

3.3. TensorFlow

TensorFlow is an open-source platform developed by Google, designed for machine learning and artificial intelligence applications. It provides a comprehensive library and flexible ecosystem of tools that allow developers to build and deploy machine learning models efficiently. TensorFlow is widely used for tasks such as natural language processing, image recognition, and deep learning, making it an essential tool for developing sophisticated AI applications, including chatbots [16].

Its scalability makes it a popular choice for integrating intelligent capabilities into digital learning platforms.

3.4. IBM Watson

IBM Watson [17] is notable for its robustness and capacity to handle vast amounts of data. It offers predefined templates tailored to various sectors, such as banking, and includes a visual dialog editor, making it accessible for non-programmers to create conversation flows easily. In [18], the authors analyze this platform alongside others in terms of functionality and usability.

To summarize, this description of AI tools used in educational chatbots will offer a technical reference guide to help select the most suitable solutions for the needs of digital universities, while also delving into the technical aspects of integrating chatbots into learning systems like Moodle.

4. Basic Concepts and Tools Used

To provide a foundation for understanding the integration of chatbots in digital learning environments, this section will cover the fundamental concepts and tools essential for developing and deploying chatbot solutions in educational contexts.

4.1. Chatbots

The first Chatbot, ELIZA, was developed by Joseph Weizenbaum at the Massachusetts Institute of Technology (MIT) in 1966. Researchers define chatbots in various ways, including terms such as conversational AI entities, virtual assistants, chatterbots, digital assistants, and chatbots. Regardless of terminology, the primary goal of a chatbot remains to simulate human conversation. [19], [20], [21].

Advancements in Artificial Intelligence (AI) and Machine Learning (ML) have positioned conversational agents as essential tools across various industries. Many organizations adopt these solutions to both reduce physical staffing needs and enable rapid, automated responses based on predefined implementation criteria [22].

A conversational agent, also known as a chatbot or dialogue system, interacts with users in natural language, enabling it to understand and respond in a way that resembles human conversation. These systems can operate through text or voice-based interactions [23].

Conversational agents are widely applied in fields such as human resources, healthcare, and education, showcasing their versatility and impact across diverse sectors [24], [25].

4.2. Moodle

Moodle (Modular Object-Oriented Dynamic Learning Environment) is a free Learning Management System distributed under the GNU General Public License. It is developed in PHP. In addition to the possibility of creating courses with integrated tools and categorizing content by course, cohort level, sub-category, etc., the platform offers the possibility of being interconnected with external tools via secure APIs.

4.3. Interoperability between the chatbot and the Moodle platform using API

An API (Application Programming Interface) is a tool enabling different systems to communicate with each other. It defines the methods by which the two systems can communicate.

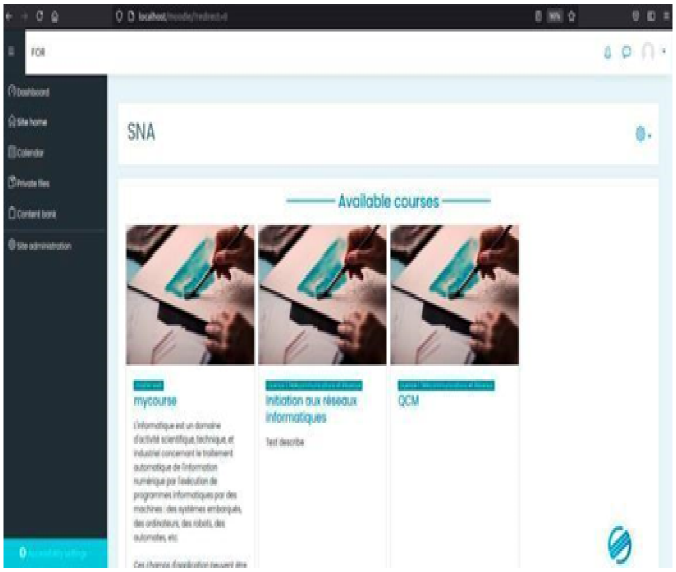
Moodle offers several APIs for interaction between the chatbot and its system. To retrieve data from the Moodle platform, authentication is required via a time-limited Token. To enable the chatbot to access the APIs, an authentication function must be implemented [26].

4.4. Natural Language Processing (NLP)

NLP (Natural Language Processing) is a branch of computer science focused on developing systems that enable computers to communicate with people using everyday language [27].

The intelligent conversation system is the foundation on which all Chatbots are built. It enables us to understand user requests and respond in a relevant way. This type of system is often built on top of an understanding and categorization algorithm. Let's now focus on the different elements of language processing: NLG (Natural Language Generation) and NLU (Natural Language Understanding).

Most chatbots operate on a basic model of these three properties, namely: Entities, Intentions, Response.



L'informatique est un domaine d'activité scientifique, technique, et industriel concernant le traitement automatique de l'information numérique par l'exécution de programmes informatiques par des machines : des systèmes embarqués, des ordinateurs, des robots, des automates, etc.

Ces champs d'application peuvent être

Figure 1: Moodle Platform Homepage

4.5. Key stages in the learning process

The first part consists of creating the NLU and discussion models, commonly known as the training phase. As Rasa is based on Machine Learning, it requires training data.

- For the NLU part (Rasa-NLU), the training data are sample sentences that the user might utter, in which intent and entities are specified. A configuration file is also required to set the algorithm parameters.
- For the discussion part (Rasa-CORE), a set of stories must be defined so that the agent learns to choose its next action. The configuration file accompanying the stories contains lists of intentions, entities, slots and actions.

4.6. Advantages of integrating chatbot into the learning system

An API (Application Programming Interface) is a tool enabling different systems to communicate with each other. It defines the methods by which the two systems can communicate.

Moodle offers several APIs for interaction between the chatbot and its system. To retrieve data from the Moodle platform, authentication is required via a time-limited Token. To enable the chatbot to access the APIs, an authentication function must be implemented.

5. Solution Implementation and Results

The implementation of a conversational agent involves several stages, including preparation and selection of the solution, development, and finally management and continuous improvement.

5.1. Chatbots

The first Chatbot, ELIZA, was developed by Joseph Weizenbaum at the Massachusetts Institute of Technology (MIT) in 1966. Researchers define chatbots in various ways, including terms such as conversational AI entities, virtual assistants, chatterbots, digital assistants, and chatbots. Regardless of terminology, the primary goal of a chatbot remains to simulate human conversation.

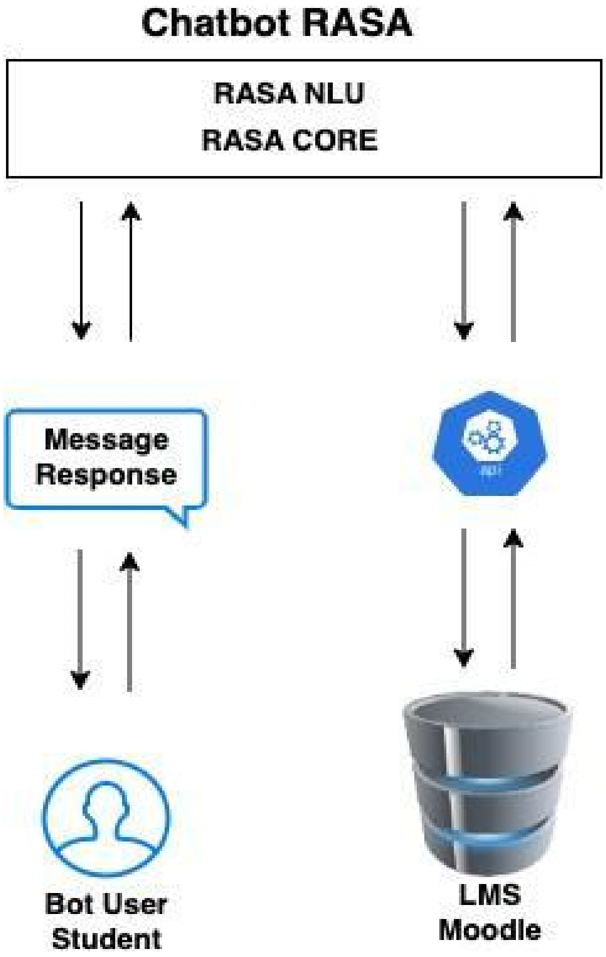


Figure 2: System architecture

5.2. Solution Development

There are several stages in the development of the solution:

- Step 1: Installing Rasa
- Step 2: Project creation
- Step 3: Defining intentions and examples
- Step 4: Defining responses
- Step 5: Creation of dialogue stories
- Step 6: Model training and testing
- Step 7: Creating the graphical interface

Once the prerequisites have been set up, the next step is to train the model and test it in console mode.

Below are additional features that we have implemented to predict the learning outcome and to personalize the learning path.

```
    $ch = curl_init();

        curl_setopt($ch, CURLOPT_URL, 'http://localhost/moodle/login/token.php?username='.$frm->username.'&password='.$frm->password.'
            &service=moodle_mobile_app');
        curl_setopt($ch, CURLOPT_RETURNTRANSFER, 1);

        $result = curl_exec($ch);

        $json_res = json_decode($result, true);

setcookie("user", $json_res['token'], time() + (86400), "/"); // 86400 = 1 day
        if (curl_errno($ch)) {
            echo 'Error:' . curl_error($ch);
        }
        curl_close($ch);
```

Figure 3: Moodle authentication and token recovery function

- **Learning Outcomes Prediction**

The objective is to leverage predictive analytics to forecast student performance based on their interactions with the chatbot. The predictive analytics model will use below data sets:

***Data Collection**:*

- Interaction Logs: Collect detailed logs of student interactions with the chatbot, including questions asked, resources accessed, and response times.
- Performance Metrics: Gather data on student performance in assignments, quizzes, and exams.
- Behavioral Data: Track engagement metrics such as login frequency, time spent on different types of content, and participation in discussions.

Predictive models:

We use regression models to predict grades or performance scores based on interaction data. The grades and performance will then be used by a neural networks model to categorize students into different performance levels (e.g., at risk, average, high performer). Finally, we applied time series analysis to monitor and predict changes in student performance over time.

Model Evaluation:

Cross-validation techniques are used to assess the accuracy and robustness of the predictive models. Precision and F1-Score are used to evaluate the models.

- **Personalized Learning Paths**

The objective of this feature is to create algorithms that adapt educational content and recommendations based on the student's progress and learning style.

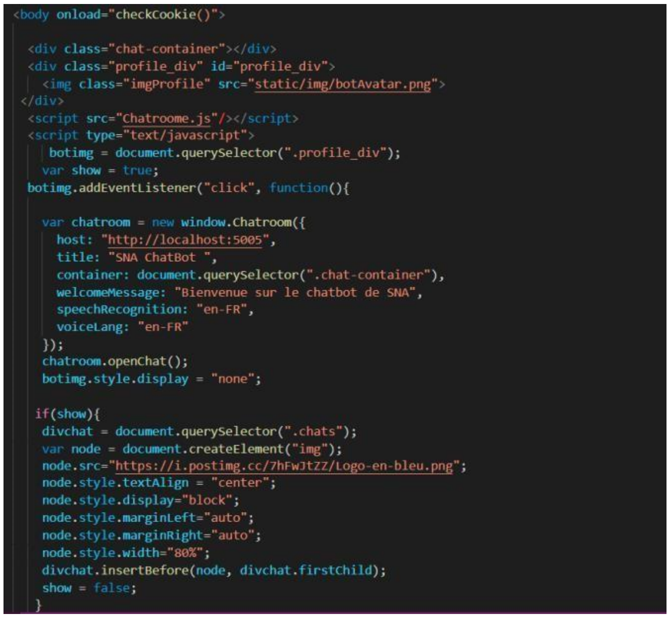
Presentation of the algorithms:

- **Content Recommendation:** Develop recommendation algorithms that suggest tailored content based on the student's learning style and knowledge level.
- **Progress Tracking:** Implement systems to continuously monitor student progress and adjust learning paths dynamically.
- **User Feedback:** Collect feedback from students on the

usefulness and relevance of recommended content to refine the algorithms.

After configuration and testing, it's important to set up a graphical interface enabling users to interact with the system. This interface defines the access parameters for the Rasa chatbot.

After finalizing the creation of the chatbot in console mode, we created the graphical interface enabling us to interact more easily with the chatbot.



```
<body onload="checkCookie()">

  <div class="chat-container"></div>
  <div class="profile_div" id="profile_div">
    <img class="imgProfile" src="static/img/botAvatar.png">
 </div>
  <script src="Chatroome.js"/></script>
  <script type="text/javascript">
    botimg = document.querySelector(".profile_div");
    var show = true;
  botimg.addEventListener("click", function(){

    var chatroom = new window.Chatroom({
      host: "http://localhost:5005",
      title: "SNA ChatBot ",
      container: document.querySelector(".chat-container"),
      welcomeMessage: "Bienvenue sur le chatbot de SNA",
      speechRecognition: "en-FR",
      voiceLang: "en-FR"
    });
    chatroom.openChat();
    botimg.style.display = "none";

   if(show){
    divchat = document.querySelector(".chats");
    var node = document.createElement("img");
    node.src="https://i.postimg.cc/7hFwJtZZ/Logo-en-bleu.png";
    node.style.textAlign = "center";
    node.style.display="block";
    node.style.marginLeft="auto";
    node.style.marginRight="auto";
    node.style.width="80%";
    divchat.insertBefore(node, divchat.firstChild);
    show = false;
   }
```

Figure 4: Code of Chatbot graphical interface

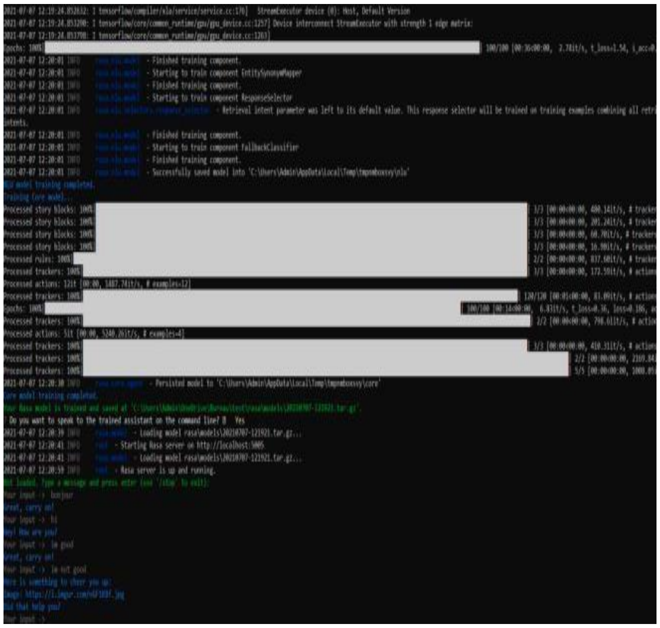


Figure 5: Model training

5.3. Steering and Continuous Improvement

Depending on the indicators set to measure the system's performance, it is important to measure the rate of understanding of the entities' performance, and to make continuous improvements by adding responses as the system is used.

5.4. Results of our studies

In this paper we have studied the impact of integrating chatbots on digital university platforms. The objective of our work was to demonstrate that the integration of chatbots into digital university platforms aims to improve the interaction between learners and educational content, while considering the specificities of distance learning. We designed and implemented a solution that allows us to validate our study.

The results of our studies show the following benefits:

First, the interactions between learners and educational content have increased significantly. This improvement is especially notable in areas such as forums activities and the facilitation of virtual classes, where the chatbot helps create a more engaging and supportive learning environment. Indeed, by providing real-time support and allowing automated responses to common questions, chatbots promote active discussions and encourages collaboration in the forums activities. The consequence of this is a reduction in dropout rates.

The other results were that we noticed the enhancement and diversification of digital content. By offering personalized content recommendations, providing interactive resources, chatbot adapts the learning experience to individual needs. This dynamic content support enhances the learning journey, making it more accessible for students.

Furthermore, the integration of the chatbot improves the assessment framework within the digital platform. By automating the formative quizzes and providing feedback, chatbots support learners in understanding and mastering core concepts, making assessments a more continuous and interactive part of the learning process.

6. Conclusion and Perspectives

To provide a foundation for understanding the integration of chatbots in digital learning environments, this section will cover the fundamental concepts and tools essential for developing and deploying chatbot solutions in educational contexts.

In this paper, we explored the integration of a chatbot into digital university platforms to enhance the interaction between learners and educational content. The chatbot, powered by Artificial Intelligence (AI), Machine Learning (ML), and built using the Rasa framework, was connected to the Moodle Learning Management System (LMS) to enable learners to self-train effectively, particularly in core IT modules. By leveraging natural language processing, this chatbot provides a seamless and intuitive way for students to access educational resources and engage with learning materials in a more dynamic and responsive manner.

As AI technology continues to evolve, our next step will be to extend the capabilities of this chatbot by integrating it with systems like ChatGPT. This will enable learners, including those outside of the Moodle platform, to ask questions and receive personalized support across various fields of study. By doing so, we aim to create a more comprehensive and accessible tool that can serve a broader range of students, making the chatbot an invaluable resource for learners across different academic disciplines.

This work allowed us to explore how the integration of chatbots into digital university platforms can help reduce dropout rates, particularly in the most demanding courses or those where the failure rate is historically high. Indeed, considering the statistics of previous studies, the use of chatbots could impact student retention in programs, by comparing the rates before and after the integration of the chatbot.

In order to strengthen the results obtained, several avenues for improvement are planned:

Integration with advanced AI systems, such as ChatGPT, to allow an even more contextualized response to student questions on various subjects.

Improvement of the user interface to further facilitate access to educational content and modules.

Development of additional features for the continuous assessment of student performance via more sophisticated predictive models.

The integration of chatbots into digital universities transforms access to educational content and improves learner engagement. Through AI and adaptive systems, students benefit from a personalized, dynamic and enriching experience, which helps improve their academic success in digital environments.

Conflict of Interest

The authors declare no conflict of interest.

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Solar Photovoltaic Power Output Forecasting using Deep Learning Models: A Case Study of Zagtouli PV Power Plant

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ABSTRACT

Forecasting solar PV power output holds significant importance in the realm of energy management, particularly due to the intermittent nature of solar irradiation. Currently, most forecasting studies employ statistical methods. However, deep learning models have the potential for better forecasting. This study utilises Long Short-Term Memory (LSTM), Gate Recurrent Unit (GRU) and hybrid LSTM-GRU deep learning techniques to analyse, train, validate, and test data from the Zagtouli Solar Photovoltaic (PV) plant located in Ouagadougou (longitude:12.30702º and latitude:1.63548º), Burkina Faso. The study involved three evaluation metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2). The RMSE evaluation criteria gave 10.799(LSTM), 11.695(GRU) and 10.629(LSTM-GRU) giving the LSTM-GRU model as the best for RMSE evaluation. The MAE evaluation provided 2.09, 2.1 and 2.0 for the LSTM, GRU and LSTM-GRU models respectively, showing that the LSTM-GRU model is superior for MAE evaluation. The R2 criteria similarly showed the LSTM-GRU model to be best with 0.999 compared to 0.998 for LSTM and 0.997 for GRU. It becomes evident that the hybrid LSTM-GRU model exhibits superior predictive capabilities compared to the other two models. These results indicate that the hybrid LSTM-GRU model has the potential to reliably predict the solar PV power output. It is therefore recommended that the authorities in charge of the solar PV Plant in Ouagadougou should consider switching to the deep learning LSTM-GRU model.

1. Introduction

In the pursuit of sustainable and renewable energy sources, solar photovoltaic (PV) systems have emerged as a leading solution for harnessing the abundant energy provided by the sun. A critical factor in optimizing the efficiency and reliability of solar PV installations is the accurate forecasting of power output [1,2]. This is particularly vital for ensuring the seamless integration of solar energy into the existing power grid and effectively managing energy resources.

The application of deep learning techniques has gained considerable attention in this context due to its capacity to model complex relationships within large datasets, offering a promising tool to enhance the precision of solar PV power output forecasting [3].

Researchers in [4] employed techniques to improve the performance of grid-connected PV systems. Financial and technical limitations emerge as hindrances to the development of PV systems, prompting a recommendation for the utilization of artificial intelligence to enhance power generation. Comparison between time series methods and artificial intelligence-based methods for power output prediction in a large grid-connected PV

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plant in China indicated the efficiency of neural network models over statistical models for PV power output prediction, particularly for short-term forecasts [5]. In a solar power prediction study in India, the efficiency of Long Short-Term Memory (LSTM) and Backpropagation Neural Network (BPNN) models was compared, confirming the effectiveness of the LSTM model [3]. LSTM and Multi-layer Perception (MLP) techniques were employed to forecast short-term solar PV power. A comparison of their performance based on parameters like Mean Absolute Errors (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R^2 revealed LSTM as the superior model [6]. A hybrid deep learning model for short-term PV power forecasting, integrating Wavelet Packet Decomposition (WPD) and LSTM, exhibits remarkable accuracy and stability. However, additional investigation is needed for long-term forecasting, especially during cloudy and rainy periods [7]. A method is proposed that combines LSTM-RNN and temporal correlation principles for PV power prediction, showcasing enhanced predictive capabilities and emphasizing the interplay between climate and electricity production [8]. The hybrid model (VMD-ISSA-GRU), integrating Variational Mode Decomposition (VMD), Improved Sparrow Search Algorithm (ISSA), and GRU, was utilized to improve PV power prediction. Results showed strong performance with an MAE of 1.0128 kW, RMSE of 1.5511 kW, and R-squared value of 0.9993 [9]. The study in [10] presents a new forecasting method for a large grid-connected PV plant in Vietnam, emphasizing climate uncertainty and employing the LSTM algorithm. The result underscored the impact of climate data on prediction accuracy, emphasizing the need for careful model configuration. The study suggests the importance of using LSTM configurations tailored to specific climatic and operational conditions. PV power generation, inherently linked to unpredictable weather conditions, poses challenges in prediction. The case studies presented reflect the ongoing efforts to develop more accurate forecasting methods to address the intermittency and instability of PV systems connected to the power grid. As per the existing literature, the LSTM model proves highly proficient in forecasting solar PV power. Moreover, its amalgamation with other models demonstrates superior effectiveness compared to the individual performance of each model.

Limited literature has been undertaken in Burkina Faso and Sahel countries in general regarding the forecasting of solar PV power using deep learning methods. This study underscores the necessity of advanced forecasting techniques using LSTM, GRU and hybrid LSTM-GRU models in predicting the output of the Zagtouli PV power. Forecasting in Zagtouli is important since more energy is needed to meet regional power demands. By delving into the challenges associated with traditional forecasting methods, the study aims to contribute valuable insights to the broader field of renewable energy research, paving the way for improved efficiency and reliability in the integration of solar power. The findings hold the potential to deepen our understanding of the dynamics influencing solar energy production and inform future developments in sustainable energy planning and management. The remainder of this paper will be structured as follows: first, the methodology, followed by the results and discussions, and finally, the conclusion and perspectives.

2. Methodology

2.1. Zagtouli PV Power Plant

The Zagtouli Solar PV Power Plant sits in Ouagadougou, the capital of Burkina Faso, positioned at a longitude of 12.30702° and latitude -1.63548°. Figure 1 depicts the location of the Zagtouli PV facility in Burkina Faso. This PV Plant has a total installed capacity of 33.696 MWp composed of 16 subsystems. In this study, one subsystem of 2.3 MW is considered.

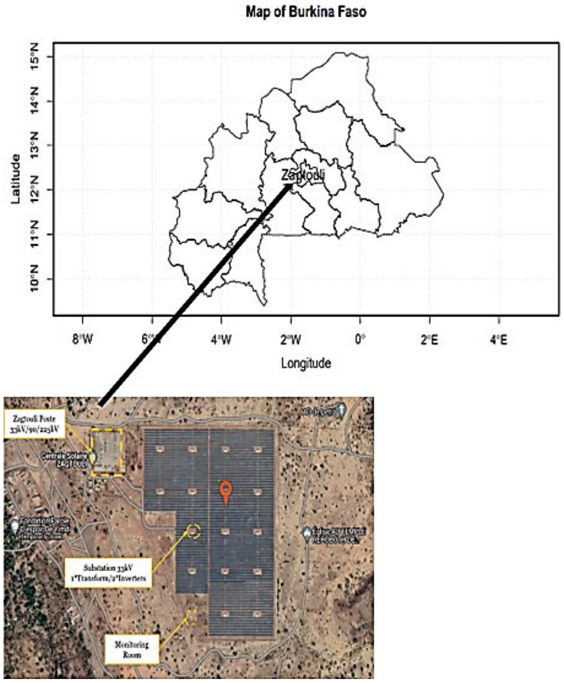


Figure 1:The Zagtouli PV Power Plant Location

2.2. Deep Learning Models

In brief, Artificial Intelligence (AI) is the endeavour to automate cognitive tasks typically executed by humans [11]. Consequently, AI constitutes a broad domain that encompasses not only Machine Learning (ML) and Deep Learning (DL) but also various other approaches that may not necessitate any form of learning [12].ML is the art of studying algorithms that learn from examples and experiences [13]. The difference from hardcoding is that the machine learns on its own to find such rules [13]. Figure 2 below shows the difference between classical programming and ML.

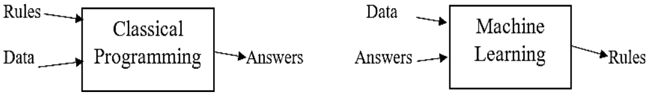


Figure 2: Difference between Classical Programming and Machine Learning.

Deep Learning (DL), a subset of Machine Learning (ML), represents a novel approach to deriving meaningful representations from data by prioritizing the acquisition of progressively more meaningful representations across successive layers [12]. Figure 3 explains the difference between AI, ML and DL.

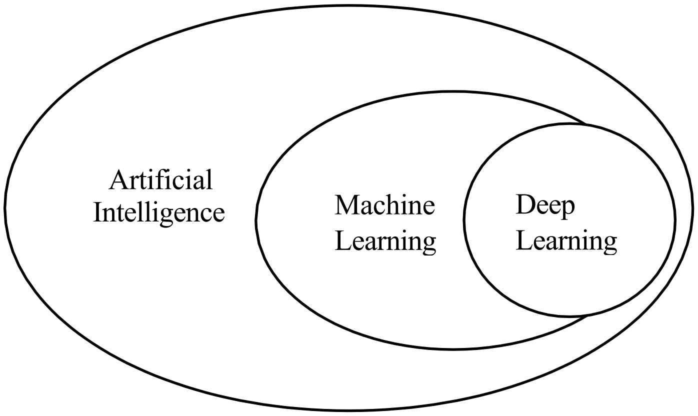


Figure 3: Artificial Intelligence, Machine Learning and Deep Learning

The DL technique is fundamentally based on the Artificial Neuron Network (ANN) which is ML method known as the artificial intelligence system which reflects the human brain. To comprehend the fundamental structure of ANN, it is essential to first grasp the concept of a 'node.' The general configuration of a node is depicted in Figure 4 below:

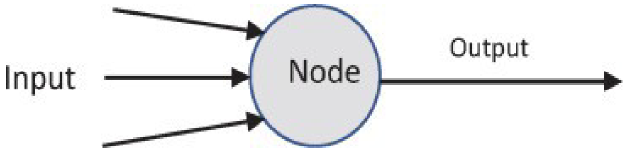


Figure 4: Basic Node Model [13]

Every node receives an array of inputs through connections and transmits them to neighbouring nodes [14]. Figure 5 depicts the overall model of an ANN, inspired by the functioning of a biological neuron [15]. Nodes are organized into linear networks referred to as layers. The ANN comprises three layers: the input layer, the output layer, and the hidden layer [16]. In the input layer, X1, X2, X3, … Xn represent multiple inputs to the network. Meanwhile, W1, W2, W3, … Wn are referred to as connection weights, indicating the strength associated with a specific node. In ANN, weights are regarded as crucial factors since they are numerical parameters that influence the interactions among neurons, playing a significant role in shaping the output by transforming the input [17]. Within the ANN, the processing component takes place in the hidden layer [17]-[19]. The hidden layer carries out two operational functions, specifically, the summation function and the transfer function, also recognized as an activation function [17,20]. The summation function serves as the initial step, where each input (Xi) to the ANN undergoes multiplication by its corresponding weight (Wi). Subsequently, the products Wi.Xi are accumulated into the summation function represented as ξ = ΣWi.Xi. The parameter 'B,' denoting bias, is employed to control the neuron's output in conjunction with the weighted sum of the inputs. This process is denoted by equation (1) below:

$$Output = \sum(Weights \times Input) + Bias \qquad (1)$$

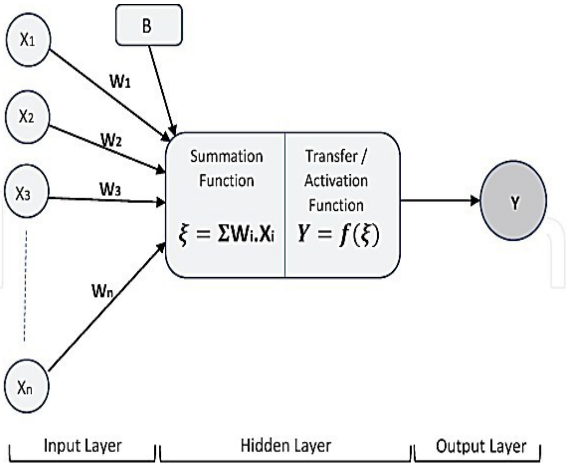


Figure 5: Generic Artificial Neural Network (ANN) model [13]

The activation function constitutes the second phase, wherein it takes the input signal from the summation function module and transforms it into the output of a node within an ANN model [14]. In general, each ANN comprises three fundamental components: node characteristics, network topology, and learning rules. Node characteristics govern signal processing by determining the number of associated inputs and outputs, the weights assigned to each input and output, and the activation function for each node. Learning rules dictate the initiation and adjustment of weights. Meanwhile, network topology defines the connectivity and organization of nodes. The operation of the ANN model involves computing the output of all neurons, representing a wholly deterministic calculation.

In this study, we will focus on two DL techniques: Long Short-Term Memory and Gate Recurrent Unit (GRU).

2.3. *Long Short-Term Memory (LSTM)*

LSTM stands for Long Short-Term Memory, and it functions as a network composed of interconnected neurons, each responsible for retaining previous state information [21]. With enough network elements, an LSTM network can conduct computations. The structure of an LSTM cell, depicted in Figure 6, comprises three key gates: the forget gate, the input gate, and the output gate. A distinctive aspect of LSTM networks is the memory cell, which serves as a repository for state information. Opening the input gate allows new information to be gathered into the cell, whereas opening the output gate leads to the erasure of past information. Within the feedback loop, the sigmoid function determines whether information should be preserved or deleted in the memory cell, while the hyperbolic tangent function manages the cell's input and output. This amalgamation of functions empowers the LSTM to selectively retain or discard information, significantly enhancing its performance. This capability makes LSTMs particularly valuable for handling temporal datasets and making predictions [22]. Notably, in LSTM networks, the final cell is transmitted to the concluding stage solely when the output gate is opened. This specific behaviour unique to LSTMs prevents gradients from dissipating rapidly within the cell, resulting in improved performance in processing time series data and generating predictions compared to other approaches.

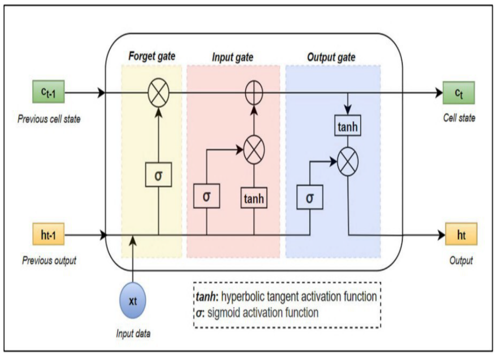


Figure 6: Long Short-Term Memory Structure [22]

2.4. Gated Recurrent Unit (GRU)

The GRU shares similarities with LSTM as it represents a more simplified and streamlined variant of the LSTM architecture. It was presented [23] by in 2014, at a time when the interest in recurrent networks was resurging within the relatively small research community. Just like the LSTM unit, the GRU possesses gating units that regulate information flow within the unit, yet it operates without distinct memory cells. The GRU lacks a mechanism to manage the extent of its state exposure, invariably revealing its entire state with each occurrence [24], [25]. Figure 7 represents the structure of the GRU model.

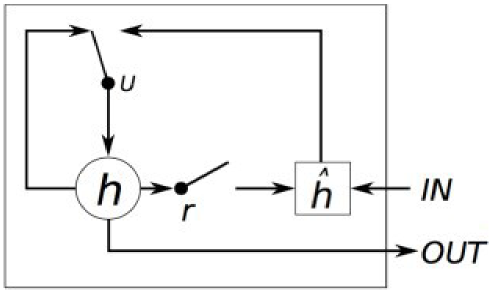


Figure 7: Gated Recurrent Unit Structure [23]

2.5. Forecasting Time

The prediction time is called the forecasting horizon [25]. Before designing the model, it is necessary to choose the appropriate forecasting horizon because the quality of the prediction is sensitive to the forecasting horizon. Prediction accuracy is influenced by the change in the forecast horizon, even with similar parameters in the same model. Figure 8 below explains the classification of PV power forecasting based on time.

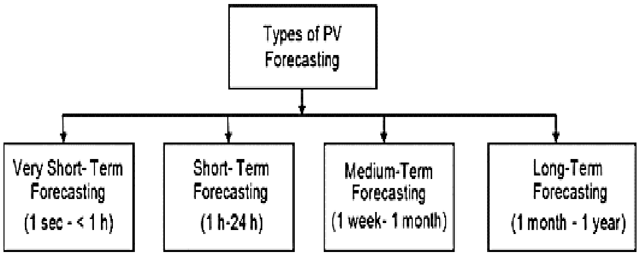


Figure 8: Classification of PV Power Forecasting Based on Time [24]

Very short-term (1sec - 1 h) forecasting is useful for real-time electricity transmission, optimal reserves, and power smoothing, while short-term (1h - 24 h) forecasting is useful for improving network security. By estimating the available electric power shortly, medium-term forecasting (1 week to 1 month) keeps the power system planning and maintenance schedule on track. Long-term forecasts (from one month to one year) aid in the planning of electricity generation, transmission, and distribution, as well as tendering and security operations.

2.6. Performance Evaluation of Forecasting Methods

Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) are widely utilized performance metrics in PV power forecasting using machine learning approaches. RMSE quantifies the average error magnitude by taking the square root of the mean of squared differences between predicted values and observed outcomes [1]. On the other hand, MAE assesses the average significance of errors in a forecast dataset by averaging the differences between actual observations and predicted outcomes across the entire test sample, with each discrepancy assigned equal weight [1]. R^2 provides a quantitative measure of the model's predictive accuracy and its capability to offer reliable estimates of future PV power output. It is important to highlight that a predictive model demonstrates increased accuracy when both MAE and RMSE are minimized, and its efficiency is enhanced when R^2 approaches a value of 1 [26]. The equations (2), (3) and (4) represent the expressions of RMSE, MAE and R^2 respectively:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)} \quad (2)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - t_i| \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - t_i)^2}{\sum_{i=1}^{N}(y_i - (\frac{1}{N})(\sum_{i=1}^{N} y_i))^2} \quad (4)$$

where yy_{ii} and t_i are the measured and corresponding predicted values of PV power and N is the number of test samples.

2.7. Data Analysis

2.7.1. Problem Framing

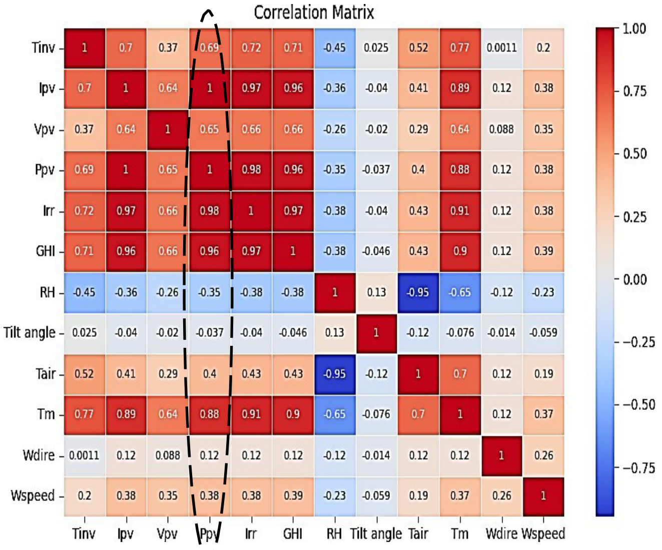
The endeavour involves the application of deep learning techniques to develop grid-connected photovoltaic solar power facilities customized for the Sahelian climate. This segment focuses on accurately predicting solar PV power generation in Burkina Faso, as it plays a crucial role in effectively managing the intermittency of solar resources to enhance grid injection. Solar forecasting emerges as a highly cost-effective method for the seamless integration of solar energy. The process entails gathering historical data from a 2.3 MWp solar PV system at the Zagtouli PV Power plant and transforming it into a spreadsheet using Microsoft Excel. System coding will be implemented using

Python, and data will be uploaded into the machine learning Toolbox for analysis.

2.7.2. Forecasting Input Variables

A set of variables were selected to perform the multivariate time series forecasting task. These variables are:

- Irradiance on an inclined plane (Irr);
- Global Horizontal Irradiance (GHI);
- Air temperature (Tair);
- Module temperature (Tm);
- PV Current (Ipv);
- PV Voltage (Vpv)
- Relative Humidity (RH);
- PV Power (Ppv)
- Title angle
- Wind direction (Wdire)
- Wind speed.



	Tinv	Ipv	Vpv	Ppv	Irr	GHI	RH	Tilt angle	Tair	Tm	Wdire	Wspeed
Tinv	1	0.7	0.37	0.69	0.72	0.71	-0.45	0.025	0.52	0.77	0.0011	0.2
Ipv	0.7	1	0.64	1	0.97	0.96	-0.36	-0.04	0.41	0.89	0.12	0.38
Vpv	0.37	0.64	1	0.65	0.66	0.66	-0.26	-0.02	0.29	0.64	0.088	0.35
Ppv	0.69	1	0.65	1	0.98	0.96	-0.35	-0.037	0.4	0.88	0.12	0.38
Irr	0.72	0.97	0.66	0.98	1	0.97	-0.38	-0.04	0.43	0.91	0.12	0.38
GHI	0.71	0.96	0.66	0.96	0.97	1	-0.38	-0.046	0.43	0.9	0.12	0.39
RH	-0.45	-0.36	-0.26	-0.35	-0.38	-0.38	1	0.13	-0.95	-0.65	-0.12	-0.23
Tilt angle	0.025	-0.04	-0.02	-0.037	-0.04	-0.046	0.13	1	-0.12	-0.076	-0.014	-0.059
Tair	0.52	0.41	0.29	0.4	0.43	0.43	-0.95	-0.12	1	0.7	0.12	0.19
Tm	0.77	0.89	0.64	0.88	0.91	0.9	-0.65	-0.076	0.7	1	0.12	0.37
Wdire	0.0011	0.12	0.088	0.12	0.12	0.12	-0.12	-0.014	0.12	0.12	1	0.26
Wspeed	0.2	0.38	0.35	0.38	0.38	0.39	-0.23	-0.059	0.19	0.37	0.26	1

Figure 9: Correlation Matrix

The Figure 9 clearly illustrates the correlation that exists between these various variables. The output variable is the output power of the PV system (Ppv), and we will focus on the correlation between this variable and others depicted in Figure 10**.**

Thus, a strong correlation can be observed with the following variables: Ipv, Ppv, Irr, GHI, Tm, Tinv and Vpv. These variables will be used as inputs.

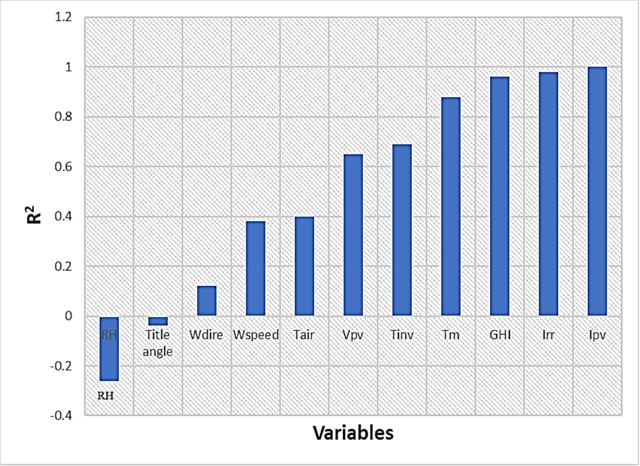


Figure 10: Correlation between Power and other Variables

Figure 11 illustrates the daily PV power trend from the 2.3 MW solar PV system at the Zagtouli power plant in May, June, July, and August 2019. Some days, notably May 4th, July 1st, July 4th, and August 3rd, saw reduced output due to cloudy conditions.

2.7.3. Data Normalization

The data's time series are all on distinct scales. To ensure that all of the features take small values on a similar scale, each feature was therefore independently normalized to have a mean of 0 and a standard deviation of 1. Because of their large range of values, target data were also normalized, just like input data. The following formula expressed by equation (5) was used to normalize the data:

$$X^k = \frac{x^k - mean}{Std} \tag{5}$$

where X^k is the normalized value of series k, xx^{kk} is the original input data value of series k, *mean* is the mean of the input data value of series k and *Std* is the standard deviation of the input data of series k.

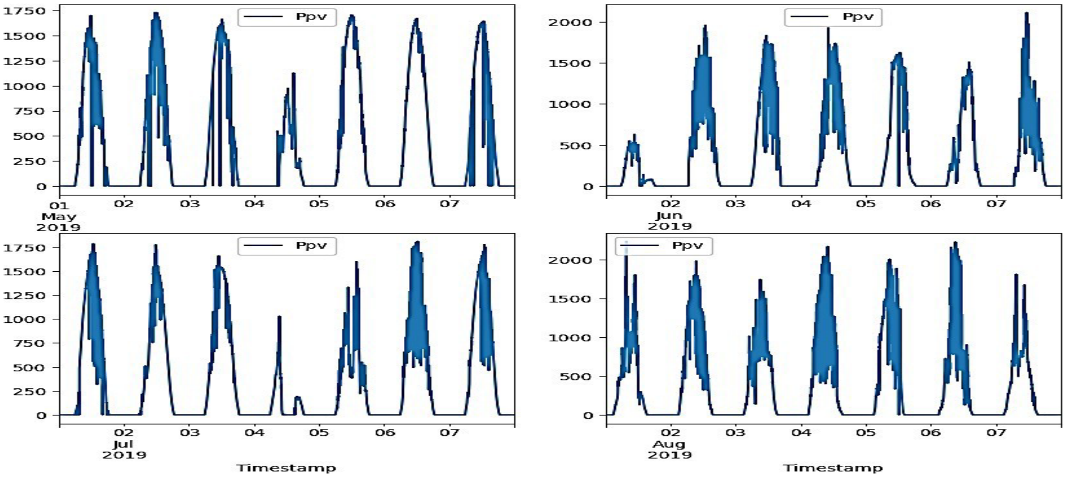


Figure 11: PV Power Evolution during the first week of May, June, July and August respectively

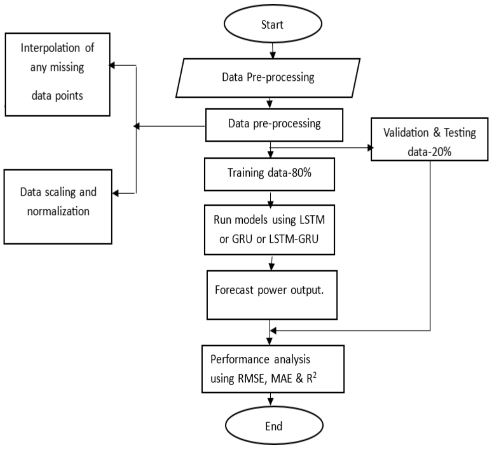


Figure 12: Flowchart of the Method

3. Results and Discussions

3.1. Models Training and Testing

The Zagtouli Solar PV System's power output was analysed using three distinct models. These models underwent training and evaluation using identical datasets for training, validation, and testing. Figures 13-15 depict the training and validation results of the LSTM, GRU, and LSTM-GRU models, respectively. The results demonstrate that the training loss curve is higher than the validation loss curve. That means the training data is more difficult to model than the validation data. The outcomes presented were achieved with the optimal hyperparameters detailed in Table 1. All models demonstrated commendable performance on the training and validation sets because lower training loss and validation loss indicate that the model fits the data correctly. Following the training phase, the finalized models were assessed using test sets, comprising data unfamiliar to the models. Unlike validation sets, test sets are utilized to gauge a trained model's performance on previously unseen data. Table 2 provides a summary of the models' test performances, measured with the RMSE, MAE and R^2 metrics, after the training. Figure 16 clearly illustrates that the hybrid model (LSTM-GRU) outperforms, followed by the LSTM and GRU models, respectively.

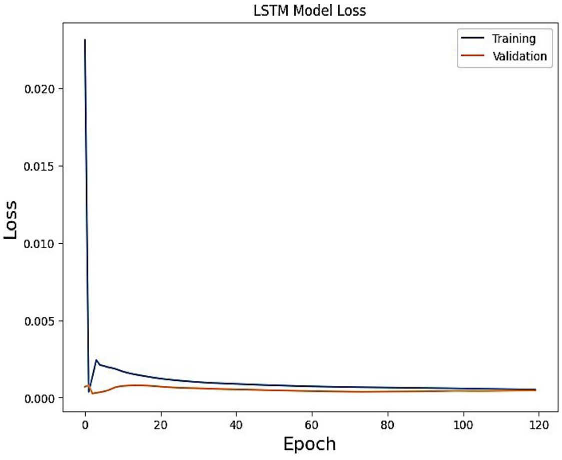


Figure 13: LSTM Model Training and Validation

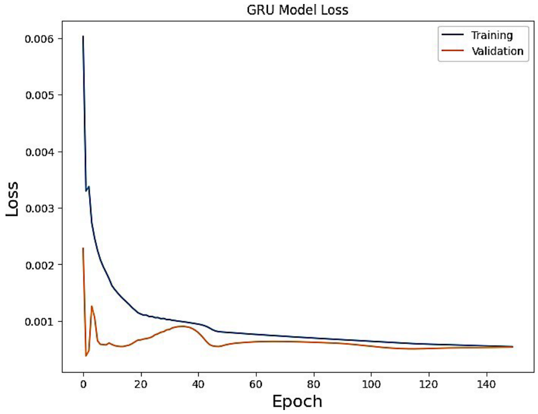


Figure 14: GRU Model Training and Validation

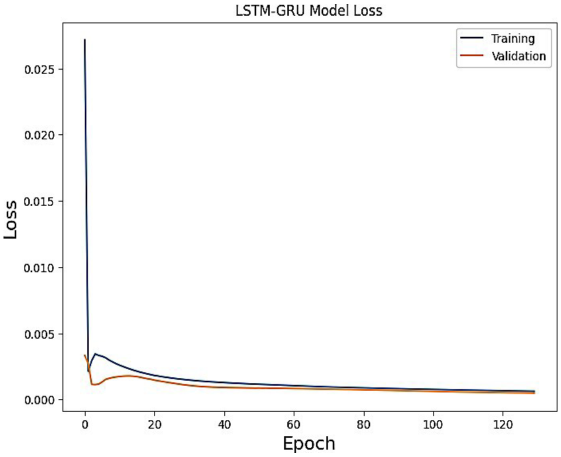


Figure 15: LSTM-GRU Model Training and Validation

Table 1. Hyper-parameters

Models	parameters	Epochs	Total Units
LSTM	37531	120	91
GRU	34601	150	101
LSTM-GRU	85626	130	181

Table 2: Test Performances using LSTM, GRU and LSTM-GRU models

Models	RMSE	MAE	R^2
LSTM	10.799	2.09	0.998
GRU	11.695	2.1	0.997
LSTM-GRU	10.629	2.0	0.999

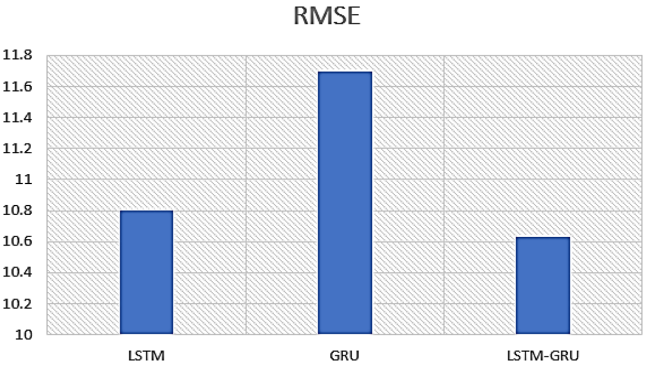


Figure 16: Root Mean Square Errors of LSTM, GRU and LSTM-GRU models

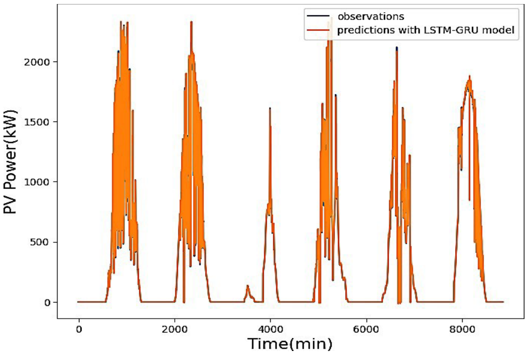


Figure 17: PV Power Forecasting vs Actual Values with LSTM-GRU

3.2. Solar PV Power Forecasting Using the Hybrid Model (LSTM-GRU)

To implement the proposed models, a dataset comprising 176,940 records was gathered within the period of 00:00 to 23:59, with minute intervals, covering the period from May 1, 2019, to August 31, 2019. The training phase utilized 80% of the data, amounting to 141,552 data points, and spanned a total of 98 days. Validation involved 15% of the data, equivalent to 26,541 data points, spanning a potential 18-day period. Testing utilized 5% of the data corresponding to 8,847 data points, covering 6 days, specifically modelled for predictive analysis. These six days were employed to predict solar PV power, and the comparison between observed and predicted values was illustrated in Figure 17 using the LSTM-GRU model. Throughout this period, a noticeable overlap between the two curves indicates the model's effectiveness in predicting the PV output power of Zagtouli's solar power plant. Notably, deep learning models showcased superior performance compared to traditional models based on statistical series.

Table 3 below shows some of the results of predicting photovoltaic power output using hybrid deep learning models around the world. The results of predictions are very sensitive to the nature of the input data used, the hidden layers number as well as the duration and period during which data were collected [27]. Given the results of Table 3, we can conclude that the LSTM-GRU prediction model for Zagtouli's solar power plant performs well.

Table 3. Comparison of some Hybrid deep learning models for PV Power Forecasting

Year	Location	Horizon	Model	RMSE	Reference
2019	Alice Springs (Australia)	1 day	LSTM-CNN	13.82	[28]
2020	Nevada (USA)	1 day	LSTM-RNN	6.29	[8]
2020	Limberg, (Belgium)	45 min	LSTM-CNN	6.404	[26]
2021	China	1day	VMD-ISSA-GRU	1.5511	[9]
2021	China	1 day	GRUP	6.83	[29]
2022	Rabat (Morocco)	1 day	LSTM-CNN	6.65	[30]
2023	Iran	12 hours	GSA-LSTM	10	[31]
2024	Zagtouli (Burkina Faso)	1 day	LSTM-GRU	10.629	Actual work

4. Conclusion and Perspectives

Predicting solar PV power effectiveness presents a viable alternative for overseeing grid-connected PV solar plants. In this investigation, we employed two deep learning techniques and their combination to forecast a system at the Zagtouli PV plant site. The hybrid model (LSTM-GRU) demonstrated superior results compared to LSTM and GRU with the RMSE metric, recording values of 10.799, 11.695 and 10.629 respectively. The data utilized for this analysis were gathered from May 2019 to August 2019, corresponding to the rainy season. In the future, data from other seasons could be employed to compare performance outcomes. This research lays the groundwork for developing an efficient and intelligent digital platform for managing the inflow of injected solar PV power into Burkina Faso's national electrical grid, aiming to secure the electrical network and optimize energy lost during continuous disconnections of power plants from the grid.

Conflict of Interest

The authors declare no conflict of interest.

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