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DEVELOPMENT OF AI IN THE CARIBBEAN: ALGORITHMS, CHALLENGES AND RECOMMENDATIONS

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Abstract. Artificial Intelligence (AI) has attracted special academic attention recently due to its potent capabilities across various application domains. Defined as the ability of computer systems to perform tasks with human-like intelligence, AI encompasses visual perception, speech recognition, decision-making, translation, and interpretation. Central to AI systems are algorithms that discover patterns and make predictions, eliminating the need for meticulous programming. The adoption of AI emerges as a pivotal tool, offering numerous advantages when harnessed and applied to detect anomalous data, which is an integral part of real-life systems. This article provides a concise overview, explicitly delving into popular AI algorithms employed in developing Anomaly Detection Systems (ADSs) applicable to Cyber-Physical Systems (CPSs), the state of AI and guidelines for adopting AI within the Caribbean region.

Keywords: Artificial Intelligence (AI); Cyber Physical Systems (CPSs); Machine Learning; Cyber Attacks; Faults; Disturbances

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JEL Classifications: O31, O33

1. Introduction

Cyber-physical systems (CPSs) can be characterized as the fusion of computational algorithms and physical components brought about by technological advancements in embedded systems, distributed systems, and advanced networking (ElBouanan et al., 2022). These systems find widespread deployment in critical infrastructures (CIs) within the Caribbean, such as gas networks, water supply, public health, transportation, and electricity generation, which are pivotal in supporting daily operations. Consequently, owing to their nature and critical importance, these systems are expected to operate seamlessly in the presence of disturbances. However, this assumption rarely holds, as CPSs comprise intricate subsystems with diverse characteristics, presenting significant challenges from a security perspective. These systems' inherent complexity and heterogeneity raise concerns regarding their vulnerability to disturbances and underscore the importance of resilient security measures. Intrinsic to these characteristics are vulnerabilities that can give rise to security threats, including the risk of cyber-attacks. Notably, cyber-attack repercussions have been observed internationally and regionally (Caribbean), specifically in the context of CPSs (Mohammed et al., 2023). Internationally, recorded cyber-attacks have demonstrated a rising trend in frequency and sophistication. Fault occurrences pose another significant challenge for Cyber-Physical Systems (CPSs), contributing to major power outages that have affected regions like the Caribbean (Mohammed et al., 2023) and on a global scale (Stefanidou et al., 2022). These faults have led to substantial disruptions, resulting in a loss of resources and potential loss of life in more severe scenarios. Therefore, cyber-attacks and fault occurrences in CPSs can be considered anomalous behaviour within such systems. Thus, this poses an ongoing challenge in anomaly detection (AD). Therefore, developing accurate Anomaly Detection Systems (ADSs) is essential for detecting the presence of anomalous behaviour and aiding in preventing such occurrences. Thus, the authors present a brief review of popular AI-based algorithms that can serve as the foundation for developing effective ADSs, which can be integrated into existing CPSs within the Caribbean region. This article focuses on three main aspects: 1) The

review of core AI strategies used for ADSs, 2) The state of AI within the Caribbean and 3) Recommendations on the way forward when harnessing AI for the Caribbean region.

2. Anomaly Detection

Anomaly Detection (AD) can be viewed as the ability to identify objects that do not possess characteristics similar to those of other data points. The process of AD has been used to investigate data identified as abnormal compared to the training data. Figure 1 highlights the AD process.

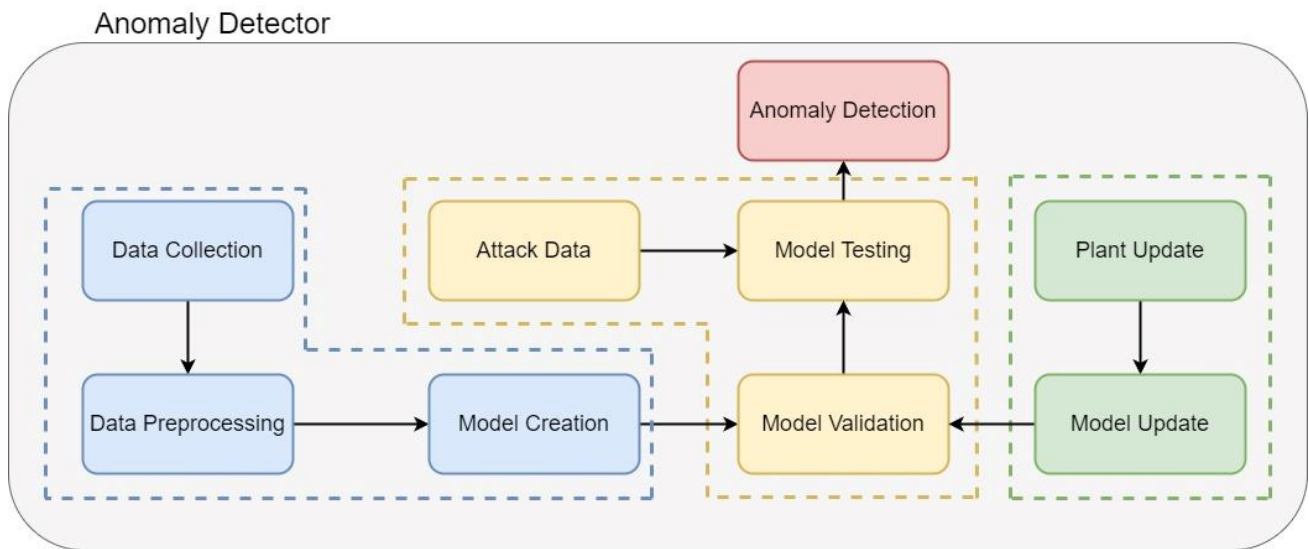


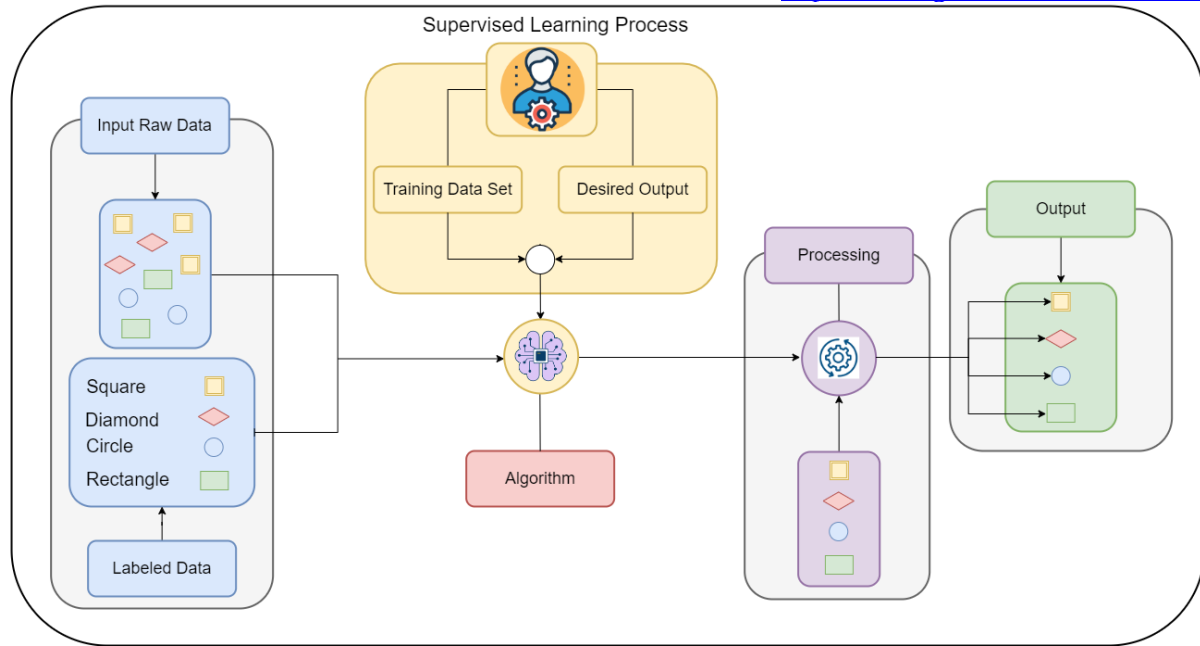
Figure 1. Anomaly Detection Process

Source: created by the authors based on literature review

The detection of anomalies is crucial to prevent the occurrence of anomalous behaviour, which can lead to the disruption of CPSs. Detection of anomalies becomes challenging when considering several factors, such as 1) inadequate anomalous data, 2) training data and 3) ever-changing environmental conditions (Natha et al., 2022). These factors must be taken into consideration. It is important to note that anomalies can be categorized into three main categories: 1) Point Anomalies, 2) Contextual Anomalies and 3) Collective Anomalies. Point anomalies can be seen as a difference at any point compared to other data flows (Jain & Kumar, 2017). Contextual anomalies can be defined as observations that can be taken as anomalous in one context but not in another, and they are accompanied by two different properties: contextual and behavioural. Lastly, collective anomalies can be seen as a group of related data instances that can be seen as anomalous compared to the entire data set (Nassif et al., 2021). The following section presents the AI algorithms typically used to develop ADSs. These include 1) Supervised Learning, 2) Semi-supervised Learning, 3) Unsupervised Learning, and 4) Deep Learning.

3. Supervised Learning Anomaly Detection (SLAD)

SLAD methods rely on information, often called the "data set," which consists of examples of input data and their corresponding desired output data. In essence, SL can be compared to a teacher-student relationship, where the training data specifies the target data set during classification for normal and anomalous data (Sowmya & Anita, 2023). SL can be broadly categorized into 1) Classification, where the output is typically a discrete variable, and 2) Regression algorithms, where the associated output is a continuous variable. Numerous common algorithms that employ this learning structure are Support Vector Machines (SVM), Decision Tree (DT), and K-Nearest Neighbour (KNN) (Siam et al., 2021). Figure 2 highlights the Supervised Learning process used within ADSs. The following methods highlight some of the typical SL algorithms used for ADSs.

**Fig. 2.** Supervised Learning Process

Source: created by the authors based on literature review

3.1. Support Vector Machine

The Support Vector Machine (SVM) was initially introduced as a kernel-based machine learning model for classification and regression tasks. Due to its discriminant power, SVMs can generate an optimal solution, contributing to their widespread popularity in AI. This method has demonstrated promising results and has been reported to outperform other supervised models. The SVM algorithm maximizes a mathematical function for a given set of data and operates based on four core concepts: 1) the separating hyperplane, 2) the maximum margin hyperplane, 3) the soft margin, and 4) the kernel function (Noble, 2006), which can affect the learning, the general performance and by extension the prediction error of the SVM anomaly detector (Siam et al., 2021). In recent times there have been several ADSs which have been proposed for time series data the optimization of feature vectors (Serkani et al., 2019), financial time series data (Shawe-Taylor & Žličar, 2015; Schmidl et al., 2022). The SVM algorithm has also been used for heartbeat time series data (Yuan et al., 2023) and an outlier detection system for network detection (Alghushairy et al., 2024). Table 1 provides an overview of the advantages and disadvantages of the SVM algorithm.

Table 1. A comparison of the SVM algorithm

Advantages of SVM	Disadvantages of SVM
Generates good results despite insufficient information about the data.	Choosing an appropriate Kernel function is difficult.
Handles nonlinear data efficiently.	Extensive memory requirement.
Solves both Classification and Regression problems.	Long training time when using large data sets.
Solves complex problems with a convenient kernel solution function.	It may be challenging to interpret and understand because of problems caused by personal factors and the weights of variables.
Relatively good scaling of high dimensional data.	

Sources: Pereira & Joshi, 2014; Marx, 2019

3.2. Decision Tree

The decision tree algorithm is used for categorical and numerical classification, representing a graph delineating decisions and their corresponding outcomes in a tree-like structure. This graphical representation comprises elements known as "nodes," consisting of three types: 1) the topmost node, designated as the root node; 2) intermediate nodes, referred to as internal nodes; and 3) leaf nodes, known as leaves. In the decision tree, the learning process unfolds from the top and is widely utilized in addressing classification problems. Notably, this algorithm is favoured for its minimal data-cleaning requirements and has gained popularity in data exploration (Patankar et al., 2016). Decision trees have been used in many ADSs to handle issues regarding anomalous financial data (Zhang, 2022), anomalous computer assessment results optimization of feature vectors (Serkani et al., 2019), network intrusion detection systems for cyber-attacks and network traffic anomalies in cellular networks (Casas, Fiadino, and D'Alconzo, 2016). Table 2 highlights some of the advantages and disadvantages of the decision tree algorithm.

Table 2. A comparison of the Decision Tree Algorithm

Advantages of the Decision Tree Algorithm	Disadvantages of the Decision Tree Algorithm
Easy to understand, very intuitive.	Overfitting, high variance algorithm. This means it can easily overfit as it has no mechanism to prevent this from creating complex decision rules.
A lower number of data preparation steps is required.	Time consuming in training phase and can be an issue if there are multiple continuous independent variables.
Redundant attributes allowing enhanced performance of the decision tree	Optimization is required; algorithm doesn't consider how recent decisions will affect stages of splitting.
Highly versatile algorithm and can perform multiple roles apart from standard predictions.	Unstable because of high variance models resulting in the accuracy of the model being affected.
Can solve nonlinear problems using complex decision boundaries.	Limited performance in regression.

Source: Patankar et al., 2016

3.2. K-Nearest Neighbour

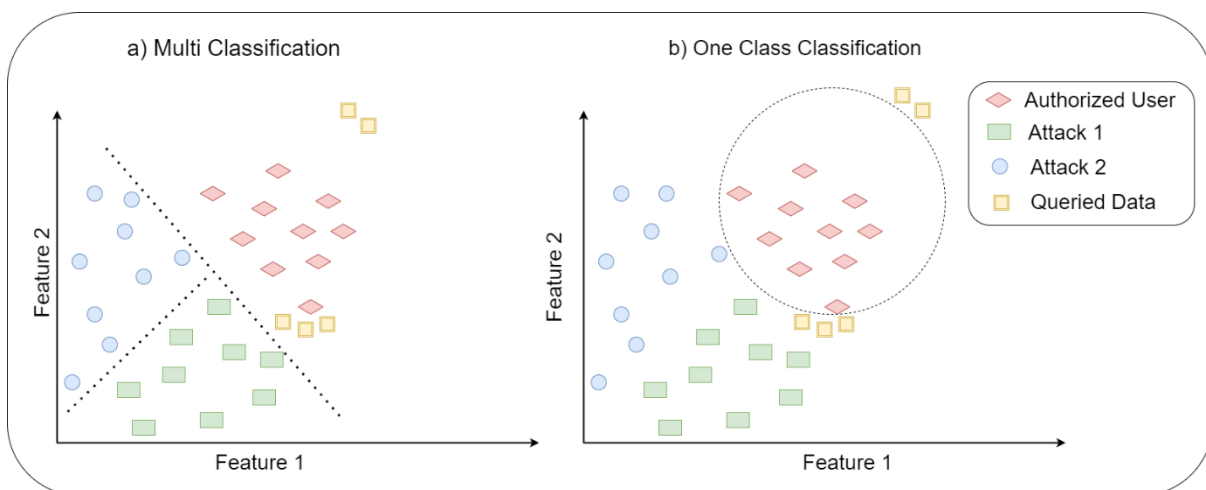
The K-Nearest Neighbour (KNN) is an algorithm known for its simplicity and effectiveness. It utilizes an input-labelled dataset, categorizing data into various classes and predicting the class of unlabelled data. KNN relies on selecting the closest neighbouring training examples for the classification process. In scenarios involving continuous data, the Euclidean distance is commonly employed to identify the nearest neighbours. When encountering new input data, KNN calculates the nearest neighbours, and the classification is determined through a majority vote. It is noteworthy that, despite its simplicity, the choice of the parameter K significantly influences the classification procedure (Taunk et al., 2019). The KNN algorithm's performance is also significantly influenced by the Euclidean distance metric and the normalization of parameters. Several methods have been proposed for KNN ADSs. The Transductive Confidence Machine KNN (TCM-KNN) algorithm has been used in network AD, highlighting its applicability using the KDD Cup 1999 dataset (Li et al., 2007). An efficient log anomaly detection method (ADM) based on improved KNN has been put forward, which handles the issue of 1) excess vector dimension, 2) unlabeled log data, and 3) an imbalance of the number of log data distorts (Ying et al., 2021). The performance of the nearest neighbour (NN) algorithm for AD has been highlighted using synthetic datasets (Gu, Akoglu and Rinaldo, 2019). A two-phased algorithm known as the one-class support vector machine (OCSVM) KNN algorithm was used to demonstrate the use of real data sets for AD (Su et al., 2015). Satellite time series anomaly detection has been proposed based on fast dynamic time warping (DTW) and improved KNN (Jrasol et al., 2023). KNN neighbours of neighbours for AD have shown enhanced performance (Nizan and Tal, 2024). Table 3 summarises the advantages and disadvantages of the KNN algorithm, offering insights into its characteristics and considerations when designing KNN ADSs.

Table 3. Comparison of KNN algorithm

Advantages of KNN	Disadvantages of KNN
Simple, comprehensible and scalable.	Expensive in determining the value of K when the dataset is large.
Computation is small compared to other algorithms.	Requires greater storage.
Effective and Efficient (Predictive Power).	Prediction phases slow for a larger dataset.
Effective for large training Data.	The computation cost is quite high.
Simple algorithm to follow and implement.	Lazy learning algorithm.

Source: Taunk et al., 2019

4. Semi-Supervised Anomaly Detection

**Figure 3.** Semi-supervised learning process

Source: created by the authors

Semi-supervised anomaly detection (SSAD) can be viewed as a method that lies between supervised and unsupervised AD. The major difference between unsupervised and supervised anomaly detection is that supervised anomaly detection uses a fully labelled dataset for training and testing, while unsupervised anomaly detection does not require a labelled dataset. This approach requires the algorithm to obtain the fundamental properties of the dataset and then score the data solely on this. Usually, this is done by some kind of density or distance estimation (Bajallan and Hashi, 2020). In SSAD, the training set is only labelled as instances of the normal class and requires no labels from the anomaly class. Figure 3 describes the semi-supervised ADM. Figure 3 highlights different data types represented by different colours. The red symbols represent an authorized user, the green and blue symbols represent anomalous data, and the brown symbols represent queried data. Multi-classification can separate the problem classes without error using established boundaries among labelled data sets. Only authorized users and attack types 1 and 2 can be detected in this method, as shown in Figure 3(a). Therefore, using the multi-classification scheme, queried data can be classified into either Authorized users or Attack data, and consequently, new types of anomalies can be classified incorrectly. However, this issue can be resolved using a one-class classification method. Setting a boundary around the entirety of the negative class ensures the classifier can distinguish patterns from an authorized user and anomalous data (Villa-Pérez et al., 2021). This type of classification can be seen in Figure 3(b). Several approaches using these techniques have been proposed (Xu et al., 2023), (Zhou et al., 2023), (Karasmanglou, Antonakakis and Zervakis, 2023), (Baradaran and Bergevin, 2024).

5. Unsupervised Learning

Unsupervised learning uses unlabeled data, allowing users to categorize data based on similarities. This technique uses a principle called "clustering", which considers the similarities in data. The training creates a situation where hidden patterns in the unlabeled dataset can be discovered. In essence, unsupervised learning

mimics human beings through learning from previous experiences. This learning style can be compared to learning without a teacher (Siam et al., 2021) and can be seen in Figure 4.

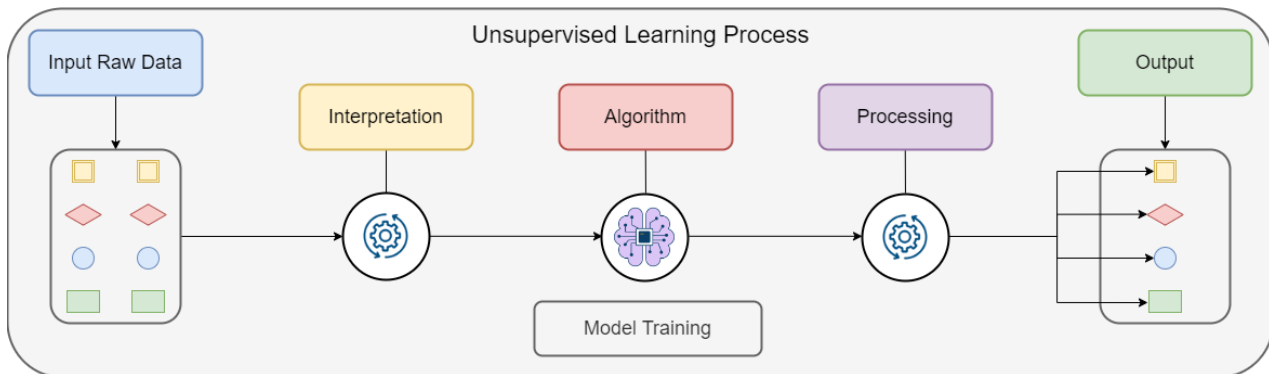


Figure 4. Unsupervised Learning Process

There are currently several popular unsupervised anomaly detection algorithms, such as 1) Nearest neighbor-based techniques, 2) Clustering-based methods, 3) Statistical algorithms and Subspace techniques. However, emphasis is placed on clustering ADMs for this section.

5.1. K means Clustering

The K-means clustering algorithm is an iterative approach that separates unlabeled data into K clusters and assigns membership for each data sample to a cluster based on similarities. The algorithm operates on the principle that data samples are allocated to the nearest centroid, making it a centroid-based method. The general flow for the K-means clustering algorithm can be described by the following four (4) points: 1) selection of K points as initialized centroids, 2) repeat the process, 3) form K clusters by assigning each point to its nearest centroid and 4) recompute the centroid for each cluster until there is no change in the centroid. For more details surrounding K means Clustering refer to (Ghosh and Dubey, 2013; Ahmed et al., 2020). Clustering can be divided into three different categories: 1) Exclusive, 2) Hierarchical and 3) Overlapping Clustering. Exclusive Clustering can be defined as a method where the data or object may only exist within a cluster. In hierarchical Clustering, this method establishes a hierarchy of clusters, which can exist as Agglomerated and divided hierarchical grouping associated with the hierarchical set. Overlapping Clustering can divide a data point into two or more groups of clusters. The following highlights some of the recent clustering ADMs which have been proposed. These methods focus on aspects such as grouping images into coherent clusters of different anomaly types (Sohn et al., 2023), using a mixed clustering approach for AD of real-time data with an emphasis on the factor of time (Mazarbhuiya & Shenify, 2023a) and an ADM for building energy consumption data, which can detect point anomalies and collective anomalies (Lei et al., 2023). Similar ADMs include an unsupervised anomaly detection algorithm (GC-ADS), which uses grid clustering and the Gaussian distribution (Zou et al., 2023), a clustering-based approach which detects real-time anomalies and handles the issue of high dimensionality of data (Mazarbhuiya & Shenify, 2023b) and an intelligent Deep Clustering-based Local Outlier Probabilities (DCLOP) approach for satellite telemetry data (Obied et al., 2023).

6. Deep Learning

Deep Learning (DL) can be seen as a complex evolution of machine learning (ML) algorithms that use layered architectures to model complex scenarios. This method uses artificial neural networks (ANNs), which mimic the human brain and produce better performance than other conventional ML techniques (Sowmya & Anita, 2023). Deep learning consists of various types of networks, such as Convolutional Neural Networks (CNNs), Restricted Boltzmann Machines (RBMs) and Recurrent Neural Networks (RNNs), each of which contains different characteristics and functionality. Essentially, these networks can learn in a supervised, semi-supervised, and unsupervised manner (Mahmud et al., 2021). The following section focuses on two DL techniques: 1) Autoencoders and 2) Long Short-Term Memory.

6.1. Autoencoders

Autoencoders can be classified as unsupervised machine learning architectures that perform both classification and address the issue of dimensionality reduction. The autoencoder network typically consists of three main components: 1) the encoder, 2) the code, and 3) the decoder. When there is an input, the encoder compresses the input, and the decoder reconstructs the compressed input. Autoencoder networks operate using the backward propagation algorithm, which helps minimize reconstruction loss. Reconstruction loss measures how close the output is to the input (Sowmya and Anita, 2023). Figure 5 highlights the structure of an Autoencoder.

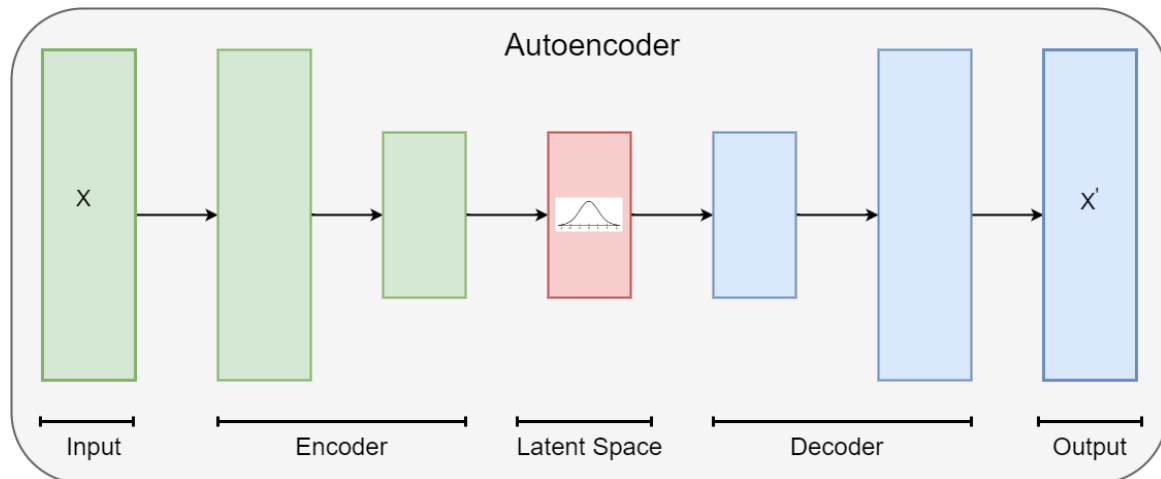


Figure 5. The Autoencoder Process

Autoencoder-based ADSs are normally trained with and are expected to recover any given input as closely as possible to the learned patterns. Thus, a situation involving a reconstruction error can be deemed an anomaly. Therefore, an auto-encoder can identify anomalies using the deviation in patterns from the training data (Song et al., 2021). There have been several autoencoder schemes which have been proposed to deal with aspects such as web attacks (Mesiar & Kolesárová, 2018), defects in concrete structures (Chow et al, 2020), visual anomaly detection (Sun, Wang, and Li, 2024), AD in cloud computing networks (Torabi et al., 2023) and fault detection (Fahmi et al., 2024).

6.2. Long Short-Term Memory (LSTM)

Recurrent deep neural networks are inherently challenging to train because of the associated exploding/vanishing gradient problem. Therefore, the LSTM model was developed to overcome these shortcomings when the issue of learning long-term dependencies is involved. The typical LSTM model comprises four (4) main components: 1) cell, 2) input gate, 3) output gate and 4) a forget gate. It is important to note that the forget gate was not initially part of the LSTM configuration but was proposed to allow the network to reset its state. The LSTM configuration contains a set of recurrently connected networks called memory blocks. The memory blocks are used to retain its state over time and regulate the flow of information. Figure 6 highlights the structure of the LSTM network configuration (Van Houdt, Mosquera and Nápoles, 2020). There have been several proposed LSTM ADMs such as convolutional long short-term memory (Conv-LSTM) which extends fully connected LSTM (FC-LSTM) to detect violent actions (Fahmi, Kashyzadeh and Ghorbani, S., 2024), fault detection utilizing LSTM with hidden dynamics and reversible instance normalization (Liu, Young, and Jafarpour, 2023) and the detection of abnormal air quality (Wei et al, 2023). Anomalous human activity detection has also been proposed using raw video streams of data facilitated by a convolutional neural network (CNN) and a bidirectional long short-term memory (Bi-LSTM) method (Kumar et al., 2023).

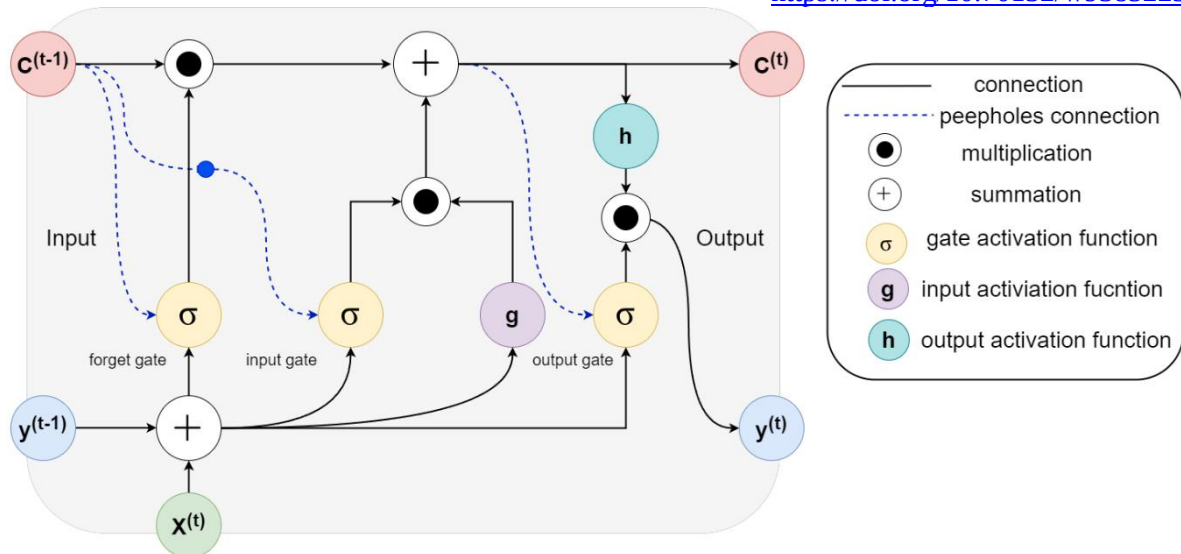


Figure 6. The Long Short-Term Memory Structure

The methods highlighted serve as an introduction to some of the critical algorithms that can be used in ADSs, tailored for various applications to ensure the detection and prevention of occurrences such as faults and cyber-attacks. Given the Caribbean's susceptible environment to faults and cyber threats, there is a demand for real-time monitoring and quick response capabilities. Implementing AI-based ADSs allows the region to manage these risks more effectively, improving its capacity to respond swiftly to disturbances that could impact CPSs and, by extension, CIs. These methods equip entities such as governments and infrastructure operators with the necessary tools to proactively identify potential threats before they can escalate into widespread failures. AI-based ADSs significantly enhance system resilience under abnormal conditions by enabling early detection and intervention. This proactive approach reduces system downtime and, in severe situations, prevents the loss of life by ensuring the continued operation of essential services. Systems such as these can improve the region's overall stability and security. Given the importance of ADSs, this raises a key question regarding the Caribbean region: What is the current state of AI within the Caribbean region? The following section addresses this question.

7. The state of AI within the Caribbean

The field of AI has been generating great interest among countries such as the United States (US) and China, competing for the top position in the global AI market. In 2017, China unveiled a plan to transform its country into a \$150 billion AI global leader, while the United States allocated \$10 billion for AI investments. However, the US has faced challenges due to limited funding. Furthermore, researchers and startup companies have been increasingly attracted to funding opportunities provided by China, impacting the strategic position of the US (Florez Zuluaga et al., 2019). While the US and China can be viewed as undoubtedly the leaders in the AI race, other countries such as the United Kingdom, France, Germany, India, Canada, and Russia are currently also showing great potential as it relates to AI initiatives (Keary, 2024).

In contrast to these global leaders, regions such as Latin America face significant challenges in AI readiness. A 2019 government AI readiness survey conducted by Oxford Insights and the International Development Research Centre (IDRC) revealed the absence of Latin American countries (LAC) being ranked amongst the top 20 countries, highlighting the Caribbean region's lack of preparedness for AI adoption (George et al., 2019). In 2023, the same study was conducted where the LAC region reported an average score of 41.50, placing it 6th among 9 surveyed regions. Figure 7 presents the Government AI readiness Index for the LAC region in 2023. It is important to note that there is a difference of 40 points recorded between the average score recorded by the LAC region and that of the North American region. There is also a major difference between the highest-ranking country within the LAC region, Brazil, with an associated score of 63.70. Haiti is recorded as the lowest-ranking country within the LAC region at a value of 21.97. This highlights the huge disparities from region to region and when comparing LAC countries within their region. Countries such as Brazil, Chile, Uruguay, Colombia,

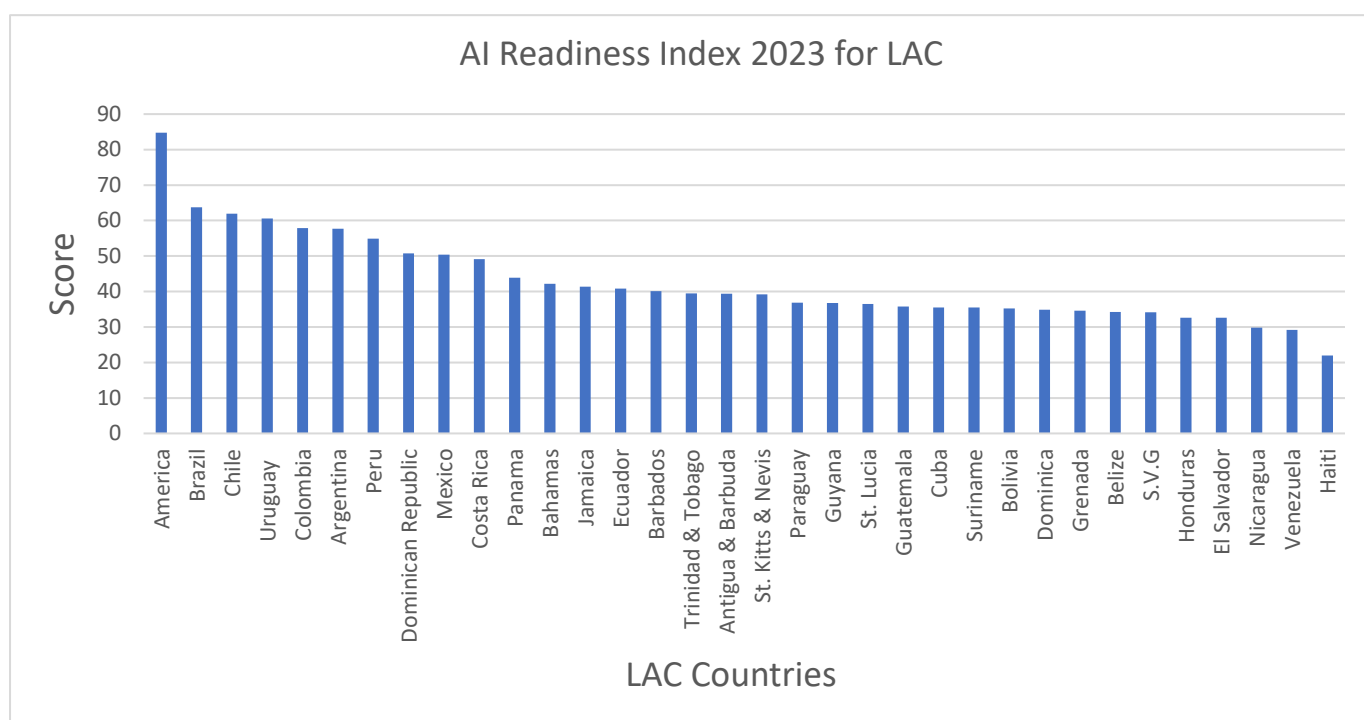
Argentina, Peru, Dominican Republic and Mexico represent 24% of the LAC with an associated score represented by the following ($50 \leq AI \text{ index score} \leq 65$). These countries represent the high-scoring nations making progress in relation to AI readiness in the region.

However, it is important to understand that much work is needed when these scores are compared to the highest-ranking nations, such as America and Canada, with associated scores of 84.80 and 77.07, respectively. The remaining 76% of LAC has an associated score of ($AI \text{ index score} < 50$) and reveals that most countries still require development in areas such as 1) Government, 2) Data and Infrastructure, 3) and the Technology sector, which requires more attention (Hankins et al., 2023).

The International Development Bank (IDB) released a report highlighting key findings from 12 LAC countries (Mexico, Costa Rica, Colombia, Ecuador, Peru, Chile, Dominican Republic, Trinidad and Tobago, Brazil, Paraguay, Uruguay, Argentina) regarding their groundwork for AI adoption. This report identified several areas requiring further attention and development, detailed in Table 4. Based on the information presented in Table 4, the Caribbean is progressing in establishing foundations aligned with government strategies, implementing digital strategies, and having open data agendas. Additionally, these countries have associated research and development and major tertiary-level institutions offering AI degrees, marking a significant step in the right direction. However, concerns exist surrounding the lack of supporting digital infrastructure, connectivity issues, and the absence of AI patents, all of which impede the region's ability to fully embrace AI (Gómez Mont et al., 2020).

In addition to the IDB report, adherence to international AI principles plays a crucial role in regional AI development. The Organization for Economic Cooperation Development (OECD) AI principles provide key benchmarks for evaluating AI research, development and deployment. These principles offer valuable insights into a country's AI landscape and help establish evidence for tracking progress. However, only seven (7) countries from the LAC region have adhered to OECD principles, with three (3) countries adhering to G20 AI principles and four (4) adhering to their country-specific principles. Table 5 presents this information in more detail. While adherence to these principles can be seen as a positive step, it alone may not be sufficient to ensure the effective deployment of AI technologies within the region. Additional concerns have been highlighted in Table 6, along with their associated ranking for each category related to the use of AI (OECD/CAF, 2022).

Recent data from 2024 indicates that AI is forecasted to contribute up to 5.4% of Latin America's GDP by 2030, compared to North America's projected 14.5%, further emphasizing that the Caribbean is lagging in AI adoption. Despite the slow uptake, the Caribbean has shown signs of technological growth, with its technological industry increasing by 5.6% since 2022. This growth is driven by the rise of technological startups in the region, valued at over US \$1 billion, offering promising potential for developing AI-related industries (Muschet & Opp, 2024). Despite progress, the slow uptake of AI in the Caribbean significantly impacts the region's ability to develop and implement sophisticated systems like ADSs, which are crucial for monitoring and safeguarding critical infrastructure. The lack of digital infrastructure, inconsistent support from local agencies, and the absence of AI research patents limit the region's capacity to build the necessary foundations for widespread AI adoption. This lag poses challenges for the development of ADS, which relies on real-time data and advanced algorithms to detect anomalies in critical sectors such as energy, transportation, and communication systems. However, with the growing number of technology startups and increasing entrepreneurial activity in the region, there is potential for the Caribbean to overcome these barriers. By strengthening digital infrastructure, investing in AI education, and fostering collaborations with international AI initiatives, the Caribbean can accelerate its progress toward developing robust ADS capabilities, ensuring the resilience of its critical systems and advancing the region's overall technological growth.

**Figure 7.** Government AI readiness Index for the LAC region 2023

Source: Hankins et al., 2023

Table 4. Major Findings from the LAC report conducted by the IDB

Number of Findings	Description of Finding
Foundations with government alignment	Most surveyed nations have established solid foundations, developing their AI systems in accordance with government efforts with a focus on connectivity, infrastructure development, national digitization strategies, open data and national AI agendas.
Digital Strategy and Open Data Agenda	All surveyed countries have a digital strategy and an open data agenda except for Trinidad and Tobago.
Supporting Digital Infrastructure	There is a lack of supporting digital infrastructure.
Connectivity	A lack of connectivity is predominant, with < 70% of the LAC population on average having internet access.
State of Cyber Security	Cybersecurity amongst these nations is making progress. However, they are ranked between 51 and 123 among 175 countries worldwide.
Research and Development	Approximately 75 % of LAC major universities have research and development for autonomous systems.
AI-related degrees	Approximately over 96% of the main universities in the LAC region offer AI degrees, with 50 % having a specialized laboratory. This is very promising for the development of skills and AI entrepreneurship. However, half of these universities are located outside the country's capital, which poses an issue in terms of knowledge dissemination and opportunities.
AI patents	The LAC region recorded the lowest level (< 1%) compared to different regions.

Table 5. LAC adherence to AI principles

LAC country establishment and adherence to the AI principles			
Country Name	OECD AI Principles	G20 AI Principles	Country Specific Principles
Argentina	✓	✓	
Barbados			
Brazil	✓	✓	
Bolivia			
Chile	✓		✓
Dominican Republic			
Colombia	✓		✓
Costa Rica	✓		
Ecuador			
Jamaica			
Mexico	✓	✓	✓
Panama			
Paraguay			
Peru	✓		
Trinidad and Tobago			
Uruguay			✓
Venezuela			

Source: the authors, based on OECD/CAF, 2022

Table 6. Major concerns and associated countries by Rank

Concern	LAC Countries	Ranking System
LAC region capacities for establishing legal and ethical frameworks for AI	Colombia, Chile, Mexico, Uruguay	Regional Leader
	Argentina, Brazil, Costa Rica, Peru	Demonstrates solid commitment
	Barbados, Ecuador, Jamaica, Panama	Demonstrates initial capacity
	Bolivia, Dominican Republic, Paraguay, Trinidad and Tobago, Venezuela	Significant effort/support advised
LAC region capacities for establishing safeguards against bias and unfairness	Colombia, Mexico, Uruguay	Regional Leader
	Argentina, Brazil, Chile, Costa Rica, Peru	Demonstrates solid commitment
	Barbados, Ecuador, Jamaica, Panama	Demonstrates initial capacity
	Bolivia, Dominican Republic, Paraguay, Trinidad and Tobago, Venezuela	Significant effort/support advised
LAC region capacities for considering the explainability of AI systems and automated decision-making	Colombia, Mexico, Uruguay	Regional Leader
	Argentina, Brazil, Chile, Costa Rica, Peru	Demonstrates solid commitment
	Barbados, Dominican Republic, Jamaica, Venezuela	Demonstrates initial capacity
	Bolivia, Ecuador, Panama, Paraguay, Trinidad and Tobago	Significant effort/support advised
LAC region capacities for promoting safety and security in public sector AI systems	Colombia, Mexico, Uruguay	Regional Leader
	Argentina, Brazil, Chile, Costa Rica, Peru	Demonstrates solid commitment
	-	Demonstrates initial capacity
	Barbados, Bolivia, Dominican Republic, Ecuador, Jamaica, Panama, Paraguay, Trinidad and Tobago, Venezuela	Significant effort/support advised

Source: the authors, based on OECD/CAF, 2022

8. Recommendations moving forward for harnessing AI within the Caribbean

AI is a powerful tool that, if harnessed correctly, can contribute holistically to the development of the Caribbean region and, by extension, LAC, leading to increased productivity and sustainability. However, achieving these outcomes is not easily accomplished. Traits such as increased productivity and sustainability can only be attained through aspects such as reflection, strategic vision, regulation, and regional coordination to create opportunities. To fully take advantage of AI, an enabling environment is crucial. This involves having suitable digital infrastructure, ensuring data availability, fostering digital skills, building innovation capacities, and promoting digital entrepreneurship. These elements collectively create the foundation for harnessing the

potential benefits of AI in the region. (ECLAC, 2023). Therefore, the authors put forward the following guidelines which can be used as key enablers for the use of AI within the Caribbean region: 1) Data usage, 2) Funding, 3) Development of internal expertise and human capital, 4) Accessing external expertise, 5) Stronger partnerships, 6) Government Involvement, 7) Development of Infrastructure, 8) Research and Development, 9) Safety and Security, 10) AI awareness.

8.1. Data Collection\Usage

Data is a crucial element for any AI project, serving as input required by machine learning algorithms to learn patterns and features. However, it's essential to recognize that not all data is equal, and steps such as pre-processing are necessary to ensure the data is accurate, reliable, and suitable for the intended application. The effectiveness of the models trained and proposed heavily depends on the quality of the data set used. AI can offer solutions to government issues and limitations related to data management, and government structures can restrict its true potential. Careful consideration of these limitations is crucial to unlock the full benefits of AI in addressing governmental challenges.

8.2. Funding for AI Projects

Funding is another critical element that is a key enabler for using AI applications in the public, private, and government sectors. It is pivotal in transitioning from concept to reality for any AI project. The availability of funds facilitates the continuous development of AI applications, enhancing their capacity to serve various industries better. Furthermore, relevant stakeholders must implement appropriate measures to manage AI funding. Complete transparency in allocating and utilizing funds is essential to ensure that resources are directed towards their intended applications. Mismanagement of funds can pose a significant challenge, potentially hindering the success of AI initiatives.

8.3. Development of AI Expertise Internally

One of a country's most valuable assets is its people. Therefore, developing skilled AI personnel and experts is vital and requires the support of upskilling and recruiting programs. Emphasis must be placed on the education system, focusing on secondary and tertiary education. At the secondary level, an introduction to AI can generate genuine interest among students who may pursue this field at a tertiary level. The education system should offer well-structured undergraduate and postgraduate degrees in AI at the tertiary level while ensuring the programs are continuously re-evaluated to provide exposure to the latest trends and technology. This allows students to study AI at the highest level, allowing them to become pioneers, entrepreneurs, and experts within the field. Moreover, in building internal capacity, governments can collaborate with the private sector to leverage their expertise and resources, strengthening these educational endeavours.

8.4. Accessing and harnessing External AI Expertise

AI is a complex field with a diverse range of experts found within the international community. Given the current AI landscape that requires substantial support, seeking relevant experts for guidance and advice is recommended. This can be facilitated through the formation of partnerships within the international community. Government involvement is crucial in this process, as governments bear the responsibility of good governance and must take a leading role in seeking necessary and relevant experts internationally and coordinating such collaborative efforts. Governments should create an environment that facilitates a seamless exchange of information between regional and international entities. This collaboration is essential to shape a landscape that is better suitable for adopting and implementing AI and leveraging the expertise and insights available globally.

8.5. Creating Stronger Partnerships for the Caribbean

The creation of local partnerships is critical for the adoption and use of AI. These partnerships should involve participation from government, public, private, and international sectors, fostering collaboration across various domains. Similarly, the government is responsible for coordinating events to ensure seamless participation from all sectors. By facilitating information sharing, these partnerships create a holistic approach that incorporates viewpoints from all sectors. This collaborative effort provides a better understanding based on past experiences with AI, ultimately contributing to more informed decision-making and effective implementation strategies.

8.6. Government Involvement/Participation

Government involvement is a critical factor in adopting and using AI, as it intersects with important issues related to governance. As discussed in points 4 and 5 previously, the government plays a central role in coordinating efforts, establishing policies, and creating an enabling environment for the effective integration of AI technologies. The active engagement of the government ensures that regulatory frameworks, ethical considerations, and strategic initiatives are aligned to harness the benefits of AI while addressing potential challenges.

8.7. Development of Infrastructure

Supporting digital infrastructure is crucial for the successful adoption and use of AI. Digital infrastructure encompasses the underlying technology and systems that facilitate the digital transformation of local societies and economies. This includes networks, servers, data centres, and other hardware and software components. A lack of supporting digital infrastructure can limit a country's success in adopting and using AI. Key elements of digital infrastructure, such as broadband networks (including optical fibre and 5G) that offer high transmission rates and volumes, reliability, and low latency, are essential for sustaining connectivity and real-time communication between the cyber and physical environments. Digital infrastructure is indispensable for achieving digital transformation initiatives like the Internet of Things (IoT), Industry 4.0, networked mobility, and cloud services (Robbins and van Wynsberghe, 2022).

8.8. Research and Development

Research and development (R&D) is key in fostering innovation and driving advancements within AI. R&D initiatives create a pathway for local talent to develop novel algorithms and models, enabling more efficient solutions to complex problems. Additionally, R&D efforts contribute to the generation of emerging technologies, the identification of existing open issues, and the ability to predict future trends in the field of AI. Investing in R&D enhances the local workforce's capabilities and positions the region at the forefront of technological advancements. It becomes a driving force for continuous improvement, ensuring that the latest research findings and innovative solutions inform the adoption and implementation of AI technologies.

8.9. Safety and Security

AI has many advantages and can be used as a powerful tool. However, understanding the ramifications of using such methods is also essential, given that AI applications are known to be susceptible to cyber-attacks, which pose a serious security concern. Inherently, AI applications are used in many real-time applications where safety is a priority. Therefore, consideration must be given to aspects such as resilience, cyber-attack detection, and isolation strategies, which must be integrated to account for abnormal behaviour when it presents itself.

8.10. AI awareness

AI awareness is essential today, given the prevalent hesitation and distrust among people. This scepticism is understandable and creates an impression that AI systems can be biased (Geoff & Ward, 2022). People must understand the benefits and disadvantages of using AI, providing them with a comprehensive view of the field. This approach allows individuals to make informed decisions based on a more nuanced understanding rather than relying on preconceived notions that may lead to inherent biases against AI. Meaningful endeavours by key stakeholders, including government, public entities, and private enterprises, are essential in providing the public with accurate and comprehensive information about AI. Such initiatives can contribute to reducing hesitancy and changing the way people currently think about AI, fostering a more informed and constructive perspective.

Conclusions

The novelty of this paper lies in its comprehensive and systemized examination of Artificial Intelligence (AI) development within the Caribbean region, offering a unique perspective on the challenges, opportunities, and practical pathways to adoption. By providing an in-depth review of popular AI algorithms tailored for Anomaly Detection Systems (ADSs) with application to Cyber-Physical Systems (CPS), the paper not only underscores the importance of these technologies in safeguarding critical infrastructure but also contextualizes their implementation within the region's technological landscape. A major contribution of this research is the

identification of ten key enablers which are designed to address the current gaps in AI readiness while providing a strategic roadmap for regional stakeholders, including governments, academic institutions, and private enterprises. Additionally, the study highlights the disparity between global leaders in AI, such as the United States and China, and the Caribbean's slower pace of adoption, emphasizing the pressing need for targeted investments and policy-driven initiatives. The emphasis on ADS as a critical tool for monitoring and protecting vital systems such as energy, water supply, and transportation further highlights the practical relevance of these findings, by focusing on region-specific challenges such as inadequate digital infrastructure, limited AI research outputs, and inconsistent policy alignment. This paper serves as a call to action for leveraging the growing technological potential in the Caribbean. It bridges the gap between theoretical AI advancements and their real-world applications in the region, providing a solid foundation for future research and development initiatives. Ultimately, this paper makes a significant contribution by laying the groundwork for a more resilient, technologically advanced Caribbean, capable of meeting the demands of an increasingly AI-driven world.

References

- Ahmed, M., Seraj, R., & Islam, S.M.S. 2020. The k-means algorithm: A comprehensive survey and performance evaluation. *Electronics*, 9(8), 1295. <https://doi.org/10.3390/electronics9081295>
- Alghushairy, O., Alsini, R., Alhassan, Z., Alshdadi, A.A., Banjar, A., Yafaz, A., & Ma, X. 2024. An efficient support vector machine algorithm-based network outlier detection system. *IEEE Access*, 12, 24428-24441. <https://doi.org/10.1109/ACCESS.2024.3364400>
- Bajallan, R., & Hashi, B. 2020. A comparative evaluation of semi-supervised anomaly detection techniques. Independent thesis <http://kth.diva-portal.org/smash/record.jsf?pid=diva2%3A1465807&dswid=-2585>
- Baradaran, M., & Bergevin, R. A. 2024. critical study on the recent deep learning based semi-supervised video anomaly detection methods. *Multimed Tools Appl* 83, 27761–27807. <https://doi.org/10.1007/s11042-023-16445-z>
- Casas, P., Fiadino, P., & D'Alconzo, A. 2016, April. Machine-learning-based approaches for anomaly detection and classification in cellular networks. <https://tma.ifip.org/2016/papers/tma2016-final50.pdf>
- Chow, J.K., Su, Z., Wu, J., Tan, P.S., Mao, X., & Wang, Y.H. 2020. Anomaly detection of defects on concrete structures with the convolutional autoencoder. *Advanced Engineering Informatics*, 45, 101105. <https://doi.org/10.1016/j.aei.2020.101105>
- Geoff, K. Ward. 2022. Recognition, Repair & the Reconstruction of “Square One”. *Daedalus*, 151(1), 153–169. https://doi.org/10.1162/daed_a_01895
- Economic Commission for Latin America and the Caribbean (ECLAC). 2023. Artificial intelligence can contribute to transforming development models in Latin America and the Caribbean to make them more productive, inclusive, and sustainable. Retrieved from <https://www.cepal.org/en/pressreleases/artificial-intelligence-can-contribute-transforming-development-models-latin-america>
- ElBouanani, H., Barakat, C., Dabbous, W., Turletti, T. 2022. Passive delay measurement for fidelity monitoring of distributed network emulation, *Computer Communications*, 195, 40-48, <https://doi.org/10.1016/j.comcom.2022.07.004>
- Fahmi, A.T.W.K., Kashyzadeh, K.R., & Ghorbani, S. 2024. Fault detection in the gas turbine of the Kirkuk power plant: An anomaly detection approach using DLSTM-Autoencoder. *Engineering Failure Analysis*, 160, 108213. <https://doi.org/10.1016/j.engfailanal.2024.108213>
- Fernandez-Blanco, E., Daniel Rivero, D., & Pazos, A. 2020. EEG signal processing with separable convolutional neural network for automatic scoring of sleeping stage. *Neurocomputing*, 410, 220-228, <https://doi.org/10.1016/j.neucom.2020.05.085>
- Florez Zuluaga, J.A., David Ortega Pabón, J., Vargas Bonilla, J. F., & Quintero Montova, O. L. 2019. Meteorological Risk Early Warning System for Air Operations, 2019 *IEEE International Symposium on Technology and Society (ISTAS)*, Medford, MA, USA, pp. 1-10. <https://doi.org/10.1109/ISTAS48451.2019.8938012>
- George, J.A., Park, S. O., Choi, J. Y., Uyangaa, E., Eo, S. K. 2019. Dual-Faced Implication of CD4 +Foxp3 + Regulatory T Cells Expanded by Acute Dengue Infection via TLR2/MyD88 <http://doi.org/10.2139/ssrn.3424186>
- Ghosh, S., & Dubey, S.K. 2013. Comparative analysis of K-means and fuzzy C-means algorithms. *International Journal of Advanced Computer Science and Applications*, 4(4), 35-39. <https://doi.org/10.14569/IJACSA.2013.040406>

Gómez Mont, C., Del Pozo, C.M., Martínez Pinto, C., & Martín del Campo Alcocer, A.V. 2020. La inteligencia artificial al servicio del bien social en América Latina y el Caribe: Panorámica regional e instantáneas de doce países. <https://doi.org/10.18235/0002393>

Gu, X., Akoglu, L., & Rinaldo, A. 2019. Statistical analysis of nearest neighbor methods for anomaly detection. 33rd Conference on Neural Information Processing Systems (NeurIPS 2019), Vancouver, Canada https://proceedings.neurips.cc/paper_files/paper/2019/file/805163a0f0f128e473726ccda5f91bac-Paper.pdf

Hankins, E., Fuentes Nettel, P., Martinescu, L., Grau, G., & Rahim, S. (2023). Government AI Readiness Index 2023. Retrieved from <https://oxfordinsights.com/wp-content/uploads/2023/12/2023-Government-AI-Readiness-Index-1.pdf>

Jain, H., & A. P. Kumar, A.P. 2017. A bottom up procedure for text line segmentation of latin script, 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Udupi, India, 2017, pp. 1182-1187, doi: <https://doi.org/10.1109/ICACCI.2017.8126002>

Karasmanoglou, A., Antonakakis, M., & Zervakis, M. 2023. ECG-based semi-supervised anomaly detection for early detection and monitoring of epileptic seizures. *International Journal of Environmental Research and Public Health*, 20(6), 5000. <https://doi.org/10.3390/ijerph20065000>

Keary, T. 2024. Top 10 countries leading in AI research & technology in 2024. Retrieved from <https://www.techopedia.com/top-10-countries-leading-in-ai-research-technology#:~:text=The%20US%20leads%20the%20way.and%20private%20and%20public%20funding>

Kumar, M., Patel, A.K., Biswas, M., & Shitharth, S. 2023. Attention-based bidirectional-long short-term memory for abnormal human activity detection. *Scientific Reports*, 13(1), 14442. <https://doi.org/10.1038/s41598-023-41231-0>

Jrasol, J., Yuelei Xu, Y., Qing Zhou, Q., Tian Hui, T., & Zhaoxiang Zhang, Z. 2023. N-fold Bernoulli probability based adaptive fast-tracking algorithm and its application to autonomous aerial refuelling, *Chinese Journal of Aeronautics*, 36(1), 356-368, <https://doi.org/10.1016/j.cja.2022.05.010>

Lei, L., Wu, B., Fang, X., Chen, L., Wu, H., & Liu, W. 2023. A dynamic anomaly detection method of building energy consumption based on data mining technology. *Energy*, 263, 125575. <https://doi.org/10.1016/j.energy.2022.125575>

Liu, Y., Young, R., & Jafarpour, B. 2023. Long-short-term memory encoder-decoder with regularized hidden dynamics for fault detection in industrial processes. *Journal of Process Control*, 124, 166-178. <https://doi.org/10.1016/j.jprocont.2023.01.015>

Li, Y., Fang, B., Guo, L., & Chen, Y. 2007, March. Network anomaly detection based on TCM-KNN algorithm. In *Proceedings of the 2nd ACM Symposium on Information, Computer and Communications Security* (pp. 13-19). <https://doi.org/10.1145/1229285.1229292>

Mahmud, T., Khan, I. A., Mahmud, T. I., Fattah, S. A., Zhu, W. -P., & Ahmad, M. O. 2021. Sleep Apnea Detection From Variational Mode Decomposed EEG Signal Using a Hybrid CNN-BiLSTM, in *IEEE Access*, vol. 9, pp. 102355-102367. <https://doi.org/10.1109/ACCESS.2021.3097090>

Mazarbhuiya, F.A., & Shenify, M. 2023a. A mixed clustering approach for real-time anomaly detection. *Applied Sciences*, 13(7), 4151. <https://doi.org/10.3390/app13074151>

Mazarbhuiya, F.A., & Shenify, M. 2023b. Real-time anomaly detection with subspace periodic clustering approach. *Applied Sciences*, 13(13), 7382. <https://doi.org/10.3390/app13137382>

Marx, S. 2019. Organizational Challenges of Digitalization Initiatives in Tourism Network Management Organizations. In: Abramowicz, W., Corchuelo, R. (eds) *Business Information Systems Workshops. BIS 2019. Lecture Notes in Business Information Processing*, vol 373. Springer, Cham. https://doi.org/10.1007/978-3-030-36691-9_14

Mohammed, A., Muddeen, F., Marine, L., & Ramlal, C.J. 2023. The exigency for resilient and cyber-secure critical infrastructure in the Caribbean. *West Indian Journal of Engineering*, 45(2), 35-49. <https://doi.org/10.47412/DEOX2766>

Siam, S. C., Faisal, A., Mahrab, N., Haque, A. B., & Suvon, M. N. I. 2021. Automated Student Review System with Computer Vision and Convolutional Neural Network, 2021 *International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)*, pp. 493-497, <https://doi.org/10.1109/ICCCIS51004.2021.9397164>

Natha, S., Leghari, M., Rajput, M.A., Zia, S.S., & Shabir, J. 2022. A systematic review of anomaly detection using machine and deep learning techniques. *Quaid-E-Awam University Research Journal of Engineering, Science & Technology, Nawabshah*, 20(1), 83-94. <https://doi.org/10.52584/QRJ.2001.11>

Nassif, A.B., Talib, M.A., Nasir, Q., & Dakalbab, F.M. 2021. Machine learning for anomaly detection: A systematic review. *IEEE Access*, 9, 78658-78700. <https://doi.org/10.1109/ACCESS.2021.3083060>

- Nizan, O., & Tal, A. 2024. k-NNN: Nearest neighbors of neighbors for anomaly detection. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (pp. 1005-1014). <https://doi.org/10.1109/WACVW60836.2024.00110>
- Noble, W.S. 2006. What is a support vector machine? *Nature Biotechnology*, 24(12), 1565-1567. <https://doi.org/10.1038/nbt1206-1565>
- Obied, M.A., Ghaleb, F.F., Hassanien, A.E., Abdelfattah, A.M., & Zakaria, W. 2023. Deep clustering-based anomaly detection and health monitoring for satellite telemetry. *Big Data and Cognitive Computing*, 7(1), 39. <https://doi.org/10.3390/bdcc7010039>
- OECD/CAF. 2022. The strategic and responsible use of artificial intelligence in the public sector of Latin America and the Caribbean. Retrieved from https://www.oecd-ilibrary.org/governance/the-strategic-and-responsible-use-of-artificial-intelligence-in-the-public-sector-of-latin-america-and-the-caribbean_1f334543-en
- Patankar, A. B., Kubde, P. A., & Karia, A. 2016. Image cartoonization methods, 2016 *International Conference on Computing Communication Control and automation (ICCUBEA)*, pp. 1-7, doi: <https://doi.org/10.1109/ICCUBEA.2016.7860045>
- Pereira, S., & Joshi, U. 2014. Implementation of support vector machine technique in feedback analysis system. *International Journal of Computer Applications*, 96(17), 24-28. <https://doi.org/10.5120/16887-6906>
- Robbins, S., & van Wynsberghe, A. 2022. Our new artificial intelligence infrastructure: Becoming locked into an unsustainable future. *Sustainability*, 14(8), 4829. <https://doi.org/10.3390/su14084829>
- Schmidl, S., Wenig, P., & Papenbrock, T. 2022. Anomaly detection in time series: A comprehensive evaluation. Proceedings of the VLDB Endowment, 15(9), 1779-1797. <https://doi.org/10.14778/3538598.3538602>
- Serkani, E., Gharaee, H., & Mohammadzadeh, N. 2019. Anomaly detection using SVM as a classifier and decision tree for optimizing feature. *The ISC International Journal of Information Security*, 11(2), 159-171 <https://doi.org/10.22042/iscure.2019.164980.448>
- Shawe-Taylor, J., Žličar, B. 2015. Novelty Detection with One-Class Support Vector Machines. In: Morlini, I., Minerva, T., Vichi, M. (eds) *Advances in Statistical Models for Data Analysis. Studies in Classification, Data Analysis, and Knowledge Organization*. Springer, Cham. https://doi.org/10.1007/978-3-319-17377-1_24
- Sohn, K., Yoon, J., Li, C.L., Lee, C.Y., & Pfister, T. 2023). Anomaly clustering: Grouping images into coherent clusters of anomaly types. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (pp. 5479-5490). <https://doi.org/10.1109/WACV56688.2023.00544>
- Song, Y., Hyun, S., & Cheong, Y.G. 2021. Analysis of autoencoders for network intrusion detection. *Sensors*, 21(13), 4294. <https://doi.org/10.3390/s21134294>
- Sowmya, T., & Anita, E.M. 2023. A comprehensive review of AI-based intrusion detection systems. *Measurement: Sensors*, 28, 100827. <https://doi.org/10.1016/j.measen.2023.100827>
- Su, J., Long, Y., Qiu, X., Li, S., Liu, D. 2015. Anomaly Detection of Single Sensors Using OCSVM_KNN. In: Wang, Y., Xiong, H., Argamon, S., Li, X., Li, J. (eds) *Big Data Computing and Communications*. BigCom 2015. Lecture Notes in Computer Science(), vol 9196. Springer, Cham. https://doi.org/10.1007/978-3-319-22047-5_18
- Sun, Z., Wang, J. & Li, Y. 2024. RAMFAE: a novel unsupervised visual anomaly detection method based on autoencoder. *Int. J. Mach. Learn. & Cyber.* 15, 355–369. <https://doi.org/10.1007/s13042-023-01913-7>
- Stefanidou-Voziki, P., Sapountzoglou, N., Raison, B., & Dominguez-Garcia, J.L. 2022. A review of fault location and classification methods in distribution grids. *Electric Power Systems Research*, 209, 108031. <https://doi.org/10.1016/j.epsr.2022.108031>
- Taunk, K., De, S., Verma, S., & Swetapadma, A. 2019. A brief review of nearest neighbor algorithm for learning and classification. In 2019 International Conference on Intelligent Computing and Control Systems (ICCS), IEEE, pp. 1255-1260. <https://doi.org/10.1109/ICCS45141.2019.9065747>
- Torabi, H., Mirtaheri, S.L., & Greco, S. 2023. Practical autoencoder-based anomaly detection by using vector reconstruction error. *Cybersecurity*, 6(1), 1. <https://doi.org/10.1186/s42400-022-00134-9>
- Mesiar, R., & A. Kolesárová, A. 2018. Aggregation functions in fuzzy set theory: History and some recent advances," 2018 6th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS), Kerman, Iran, 2018, pp. 94-97. <https://doi.org/10.1109/CFIS.2018.8336641>
- Muschet, M., & Opp, R. 2024, March 6. AI revolution is here: How will Latin America and the Caribbean respond? Retrieved from <https://www.undp.org/latin-america/digitalhub4/blog/ai-revolution-here-how-will-latin-america-and-caribbean-respond>

Van Houdt, G., Mosquera, C., & Nápoles, G. 2020. A review on the long short-term memory model. *Artificial Intelligence Review*, 53(8), 5929-5955. <https://doi.org/10.1007/s10462-020-09838-1>

Villa-Pérez, M.E., Alvarez-Carmona, M.A., Loyola-Gonzalez, O., Medina-Pérez, M.A., Velazco-Rossell, J.C., & Choo, K.K.R. 2021. Semi-supervised anomaly detection algorithms: A comparative summary and future research directions. *Knowledge-Based Systems*, 218, 106878. <https://doi.org/10.1016/j.knosys.2021.106878>

Wei, Y., Jang-Jaccard, J., Xu, W., Sabrina, F., Camtepe, S., & Boulic, M. 2023. LSTM-autoencoder-based anomaly detection for indoor air quality time-series data. *IEEE Sensors Journal*, 23(4), 3787-3800. <https://doi.org/10.1109/JSEN.2022.3230361>

Xu, H., Wang, Y., Pang, G., Jian, S., Liu, N., & Wang, Y. 2023. RoSAS: Deep semi-supervised anomaly detection with contamination-resilient continuous supervision. *Information Processing & Management*, 60(5), 103459. <https://doi.org/10.1016/j.ipm.2023.103459>

Ying, S., Wang, B., Wang, L., Li, Q., Zhao, Y., Shang, J., Huang, H., Cheng, G., Yang, Z., & Geng, J. 2021. An improved KNN-based efficient log anomaly detection method with automatically labeled samples. *ACM Transactions on Knowledge Discovery from Data (TKDD)*, 15(3), 1-22. <https://doi.org/10.1145/3441448>

Yuan, X., Chen, S., Zhou, H., Sun, C., Yuwen, L. 2023. CHSMOTE: Convex hull-based synthetic minority oversampling technique for alleviating the class imbalance problem. *Information Sciences*, 623, 324-341, <https://doi.org/10.1016/j.ins.2022.12.056>

Zhang, Q. 2022. Financial data anomaly detection method based on decision tree and random forest algorithm. *Journal of Mathematics*, 2022, 1-10. <https://doi.org/10.1155/2022/9135117>

Zhou, F., Wang, G., Zhang, K., Liu, S., & Zhong, T. 2023. Semi-supervised anomaly detection via neural process. *IEEE Transactions on Knowledge and Data Engineering*, 35(10), 10423-10435. <https://doi.org/10.1109/TKDE.2023.3266755>

Zou, B., Yang, K., Kui, X., Liu, J., Liao, S., & Zhao, W. 2023. Anomaly detection for streaming data based on grid-clustering and Gaussian distribution. *Information Sciences*, 638, 118989. <https://doi.org/10.1016/j.ins.2023.118989>

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