ESARBICA JOURNAL

JOURNAL OF THE EASTERN

AND SOUTHERN AFRICA

REGIONAL BRANCH OF THE

INTERNATIONAL COUNCIL ON

ARCHIVES

Volume 41
2022

ISSN 2220-6442 (Print), ISSN 2220-6450 (Online)

https://dx.doi.org/10.4314/esarjo.v41i1.11

Infrastructure for the implementation of artificial intelligence to support records management at the Council for Scientific and Industrial Research in South Africa

Mashilo Modiba
University of South Africa
modibmt@unisa.ac.za
Orcid ID: http://orcid.org/0000-0003-2843-0056

Patrick Ngulube
University of South Africa
ngulup@unisa.ac.za
Orcid ID: https://orcid.org/0000-0002-7676-3931

Ngoako Marutha
University of South Africa
emarutns@unisa.ac.za
Orcid ID: https://orcid.org/0000-0002-5679-4394

Received: 30 April 2021
Revised: 31 March 2022
Accepted: 30 June 2022

Abstract

This study sought to investigate artificial intelligence (AI) infrastructure required to manage records at the Council for Scientific and Industrial Research (CSIR) in South Africa. AI algorithms are used to assist robotic machines in performing their functions effectively and efficiently across different disciplines, including archives and records management. Convergent mixed-methods research was conducted, and data were collected using interviews and questionnaires. Data were analysed thematically and statistically and presented in tables and figures. The study revealed that AI infrastructure was a prerequisite for providing high-quality records management services at CSIR. However, the records management practitioners lack the knowledge and skills required to implement AI infrastructure for records management effectively. The study proposes a framework to guide the application of AI by CSIR. The proposed framework will specify the AI infrastructure required and AI application to the management of records at CSIR. It is hoped that the proposed framework will serve as a benchmark and guideline for the implementation of AI in the archives and records management industry.

Keywords: artificial intelligence infrastructure, automated classification, machine learning, natural language processing, Council for Scientific and Industrial Research

Introduction and background

Artificial intelligence (AI) infrastructure algorithms are used to assist robotic machines in performing their functions effectively and efficiently across different disciplines, including records management (Keily and Hamm, 2013). AI infrastructure could assist CSIR in providing high-quality records management services by robotically managing its records. AI infrastructure is steadily penetrating diverse aspects of human intelligence, and it has become clear that it will play an increasingly important role in records and information management services in future. AI infrastructure makes machine learning possible, and AI encompasses anything from Apple's Siri to Amazon Go, self-driving vehicles and autonomous weapons (Modiba, Ngoepe and Ngulube, 2019; Wang and Siau, 2019). AI infrastructure enables robotic machines to retrieve records efficiently and effectively, thus ensuring that organisations have easy access to information (Jackson, 2011). This means that AI infrastructure could assist robotic machines in providing high-quality records management services at CSIR. In this context, AI infrastructure includes technology that facilitates automated classification, automated digitisation, machine learning and natural language processing (NLP), and it uses automated rules, black box systems, neural networks and deep learning (Jackson, 2014; Prigg, 2017).

Automated classification

Automated classification is the application of categories, labels, tags or metadata to content to ensure that records are always stored in the right place for quick and easy retrieval. This form of classification is done by using fingerprinting and/or linguistic analysis (Woordward, 2018; Lepak, 2019). Artificial intelligence technology (AIT) has the capacity to classify records electronically for easy retrieval via an automated classification platform (Gao, Wang, Chia and Tsang, 2010). Automated classification algorithms are used to classify a specific document following a predefined rule set. The rule set might be based on a given list of similar keywords or expressions found in the content, or the algorithm might recognise some other distinctive feature of the record and base its classification on that feature (Gao et al, 2010). Parmenter (2019) explains that AI has made massive strides in developing computer vision, which is the capability of computers and systems to identify what they see and reach a conclusion. The field of document management uses optical character recognition (OCR) technology, which is a form of computer vision technology that enables a document management system (DMS) to read the content of a file and robotically organise and internalise it, without human involvement (Ripcord Company, 2019). The more files AI reads, the more it learns how employees interact with files, and the better it becomes at recognising and internalising information (Richardson, 2020; Tredinnick and Laybats, 2020). Software developed by Nuance Document Imaging, which is now part of Kofax’s Intelligent Automation Platform, uses OCR to scan files easily and quickly, and to convert paper records into actionable digital information (Parmenter, 2019).

Machine learning

Cohen, Cohen, West and Aiken (2003) and Kalaiselvan, Sharma and Gupta (2021) explain that machine learning uses statistical methods to facilitate computer learning. Machine learning happens when AI systems learn robotically and improve automatically through experience, interaction, and access to data. As a result, many software applications do not need to be explicitly programmed by humans. Machine learning focuses on the development of computer programs that can access and use data to learn without human involvement (Ali, Naeem and Bhatti, 2020). This means if records management practitioners are editing documents together, the computer can infer that they have a stronger association with one another than with someone who has never worked on a file with them (Woordward, 2018). Tredinnick (2017) explains that machine learning procedures allow the computer program to learn gradually more autonomously based on examples, and to improve its own developing logic and results without being reprogrammed. Others go so far as to attribute inventiveness to AI as machine learning algorithms can find new solutions to challenges independently (Prigg, 2017; Jarrahi, 2019).

Once links between data have been established, the computer can figure out a lot about work preferences and performance, generating a pattern that can be used in future cases (Jackson, 2011). This pattern allows links among records to be recognised and reduces the number of classification faults because it teaches the computer how files should be classified based on their content (Cohen et al, 2003; Lepak, 2019). It may also assist in grouping together similar data, such as all content associated with a specific client, which advances efficiency and the partnership experience, and helps organisations to be more compliant (Gao et al, 2010).

Natural language processing

Natural language processing (NLP) is an AIT based on links between computers and human (natural) language (Woordward, 2018; Kalaiselvan et al, 2021). It converts words into code that can be analysed by computers (Melton and Hripsak, 2005). NLP focuses on enabling computers to internalise massive amounts of natural language data using linguistic analysis (Melenhorst, Rogers and Caylor, 2001). As such it plays an important role in a wide variety of digitisation functions, but only a few of these are relevant to records management. NLP can be used to recognise concepts and metadata that are relevant to the file, as if an individual had physically read and selected concepts; it is therefore not only used to recognise concepts that occur regularly in a file (Melton and Hripsak, 2005). NLP algorithms can recognise links between named attributes (Perc et al, 2019). For instance, it can extract the name of an individual from the file or identify a division that is not mentioned in the document (Gao et al, 2010). NLP algorithms are used by search engines such as Google and YouTube, which are examples of applications used in the library and information services (LIS) sector that already employ AI as a matter of course. NLP assists in designing subject indexing, bibliometrics and information retrieval systems, therefore it plays key role in the creation of digital libraries (Cox, Pinfield and Rutter, 2019; Ali et al, 2020).

Automated rules

According to Melton and Hripsak (2005) and Woordward (2018), automated rules allow computers to perform monotonous activities on behalf of records management practitioners. For instance, when a record is classified as a contract, a preservation agenda can be robotically applied (Perc et al, 2019). An automated rules algorithm that employs fingerprinting and/or linguistic analysis enables a computer to recognise triggers robotically and to apply the correct rules – as a result, records management practitioners no longer need to be directly involved in repetitive, monotonous activities (Jackson, 2011; Lepak, 2019).

Black box

A black box is a device, system or object that can be viewed in terms of its inputs and outputs (vectors), without any knowledge of its internal workings (Montavon, Samek and Muller, 2018). In microeconomic theory, a firm is depicted as a “black box” that consists of a set of production functions or even presumed production activity with a finite set of inputs that must be adjusted to produce a set of outputs that corresponds to a maximal level of profits or some other measure of owner utility (Andersson and Johansson, 2018). Liu (2011) states that black box digitisation is connected to NLP and classification. It is another type of digitisation that tracks relationships between data and predicts subsequent data. For instance, it can indicate how many times a word appears in a file or identify relevant concepts using linguistic analysis. One document can then be linked to similar files based on their fingerprints or common characteristics (Perc, Ozer and Hojuik, 2019). When other files match the fingerprint of a document, conclusions are reached about the metadata that might apply to those files (Woordward, 2018). The relationship between content and data can then be confirmed to ensure that files are classified correctly (Nadkarni, Ohno-Machado and Chapman, 2011).

Neural network

Neural networks mimic the human brain through sets of algorithms and form an integral part of AI and machine learning (Montavon et al, 2018). They are to some extent modelled on the structure of the human brain (Abiodun, Jantan, Omolara, Dada, Mohamed and Arshad, 2018). These networks allow computer programs to recognise patterns and solve problems (Perc et al, 2019). They consist of abstracted models of interconnected neurons whose special arrangement and linking can be used to solve computer-based application problems in various field, including statistics, technology and economy (Mijwel, Esen and Shamil, 2019). Neural networks advance engagement on classification by looking at other instances where a class has been applied, as in fingerprinting (Jackson, 2011; Woordward, 2018). Neural network algorithms are tools that assist records management practitioners in organising content for records management purposes. They minimise classification errors and ensure that suitable preservation policies are applied (Liu, 2011).

Deep learning

Deep learning is a kind of machine learning and in this context, it uses a hierarchy of items, such as a classified file plan, to categorise content (Liu, 2011; Woordward, 2018). It is a subcategory of machine learning that involves the application of artificial neural networks and algorithms to learn from vast amounts of data (Viera, Pinaya and Mechelli, 2017). Deep learning algorithms enable machines to solve complex problems even when a very diverse, unstructured and inter-connected data set is used (Ali et al, 2020). For example, as a result of deep learning, a legal contract is first recognised as a legal file based on fingerprinting and/or linguistic analysis. Thereafter the machine only takes into account categories relating to law to determine that the document must be classified as a contract (Viera et al, 2017). This may need to be repeated over numerous classification sheets, but in every instance the preceding sheets will inform the subsequent classification sheet (Cohen et al, 2003; Gao et al, 2010).

Problem statement

The problem that led to this study is that research institutions such as CSIR lack the AI infrastructure required to implement AI for records management. AI infrastructure would assist CSIR in managing its records effectively and efficiently if properly applied. However, without proper AI infrastructure, CSIR would not be able to use AI for high-quality records management. As a result, CSIR would not be able to achieve its objectives. Without effective records management, CSIR would not be able to participate in global research and innovation, which is its primary objective (Patterton, 2017). Hence, CSIR needs AI infrastructure to manage its records effectively. However, the electronic records management equipment is also not effective in managing records properly due to the challenges the system encounter such as system overload and system crash.

CSIR needs to manage its records effectively using AI and robotic machines if it wishes to remain relevant in the global research and innovation arena. It therefore needs proper AI infrastructure (EE Publishers, 2017), including black boxes, that would facilitate automated classification, machine learning, deep learning, the creation of neural networks and natural language processing. Hence, this study proposes a framework to support the implementation of AI for the management of records at CSIR.

Purpose and objectives of the study

The purpose of this study was to investigate infrastructure for the implementation of AI to support the management of records at CSIR in South Africa. The specific objectives were to:

- identify the infrastructure required to implement AI for records management at CSIR in South Africa.
- propose a framework for the application of AI infrastructure for records management at CSIR in South Africa

Research methodology

Convergent mixed-methods research was conducted, and data were collected using interviews and questionnaires. The study was conducted from the perspectives of ontological pluralism and epistemic pragmatism. A convergent design was selected to allow researchers to collect both qualitative and quantitative data from participants, analyse the data independently and combine the responses during data interpretation. The study further used parallel sampling as sampling technique to collect qualitative and from the same population, but using different samples (Creswell and Creswell, 2018; Creswell and Plano-Clark, 2018).

Records management practitioners and record managers were the population of this study. They provided information about their knowledge, expertise, and expectations regarding the use of AI for records management. The population of this study consisted of a sample size of eight (8) respondents, all of whom were employed by CSIR. The respondents were one (1) portfolio manager, one (1) records manager, three (3) indexers, two (2) archives technicians and one (1) data librarian. The portfolio manager and records manager contributed qualitative data to the study through interviews. Three (3) indexers, two (2) archives technicians and one (1) data librarian contributed quantitative data to the study through questionnaires.

Findings of the study

The findings of this study are based on its objectives.

Availability of electronic records management equipment
Organisations need the right equipment if they wish to manage their records effectively and efficiently. Hence, respondents were asked about the availability of electronic records management equipment to manage records at CSIR. Five respondents indicated that CSIR had a database, five indicated it had internet and five indicated it had servers. Six respondents indicated that CSIR had network connectivity, five indicated they it a website, five indicated that CSIR had computers and six indicated that CSIR had electronic records management equipment that was used to manage records. None of the respondents indicated that there were no robotic machines for the management of records at CSIR. (See Figure 1.)

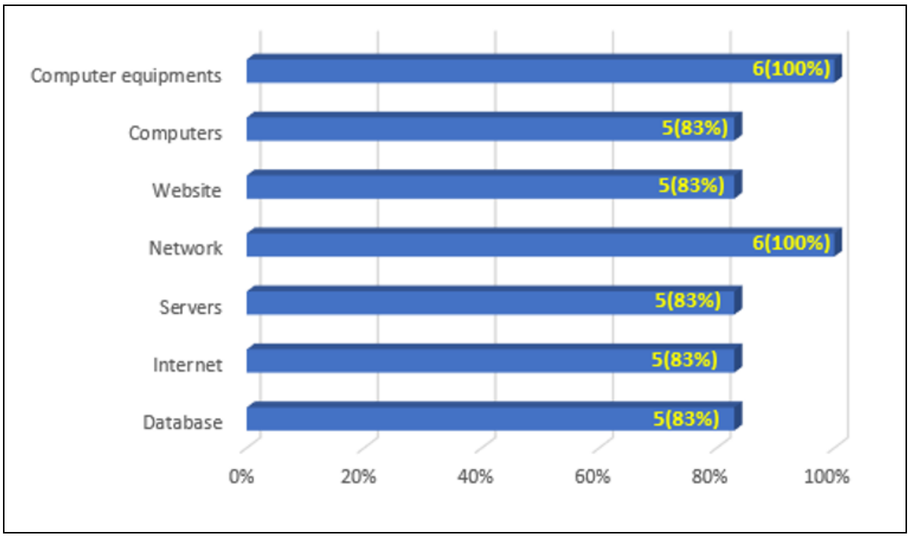

Figure 1: Electronic records management equipment (N = 6)

Rating of the effectiveness of AI infrastructure for records management

The respondents were asked if they either agreed, were unsure or disagreed with statements on the effectiveness of AI infrastructure used for records management at the CSIR. One respondent agreed that the AI infrastructure was effective in the creation of records, three respondents were unsure and two disagreed. Four respondents agreed that AI infrastructure was effective in storing records, two were unsure and none disagreed. Three respondents agreed that AI infrastructure was effective in records classification, three were unsure and none disagreed. Four respondents agreed that AI infrastructure was effective in records maintenance, two were unsure and none disagreed. Three respondents agreed that AI infrastructure provided effective records movement and security, three were unsure and none disagreed. Two respondents agreed that AI infrastructure was effective in disposing records, four were unsure, while none disagreed (See Table 1).

Table 1: Effectiveness of AI infrastructure for records management at CSIR (N=6)

ARTIFICIAL INTELLIGENCE INFRASTRUCTURE FOR RECORDS MANAGEMENT		**RATINGS**		
		AGREE	**UNSURE**	**DISAGREE**
AI infrastructure is effective in records creation	No	1	3	2
AI infrastructure is effective in storing records	No	4	2	0
AI infrastructure is effective in records classification	No	3	3	0
AI infrastructure is effective in records maintenance	No	4	2	0
AI infrastructure provide effective records movement and security	No	3	3	0
AI infrastructure is effective in disposing records	No	2	4	0

Interviewed participants were asked how AI infrastructure could be used for records management in general. They indicated that AI infrastructure could be used to provide fast, accurate and reliable outcomes in records management. Participants further stated that AI infrastructure could be used to digitise records. Responses were as follows:

Participant 1:

AI infrastructures are used because it is accurate, reliable and faster when performing activities.

Participant 2:

AI infrastructure provides high-quality metadata and also accurate results for the provision of effective and efficient records management services.

The respondents were also asked to elaborate on the issue of effectiveness of AI infrastructure in records creation. Respondents indicated that the utilisation of AI infrastructure would lead to effective records management. Responses were as follows:

Respondent 1:

AI infrastructure will do quality control during the creation of records.

Respondent 2:

AI will also assist in reading data and AI infrastructure will monitor the movement of records and keep records safe.

Respondent 3:

Through AI, records will be stored in the cloud and AI infrastructure will assist in disposing of records at CSIR.

Respondent 4:

AI infrastructure will be programmed to classify records.

Respondent 5:

AI infrastructure will ensure that records are maintained.

Respondent 6:

I don't know what AI infrastructure can do for records management.

Artificial intelligence infrastructure for records management

The study was conducted to determine participants' level of understanding of the AI infrastructure required to manage records at CSIR. One participant (17%) indicated that they knew about the following: Oracle AI, natural language processing and deep learning**.**

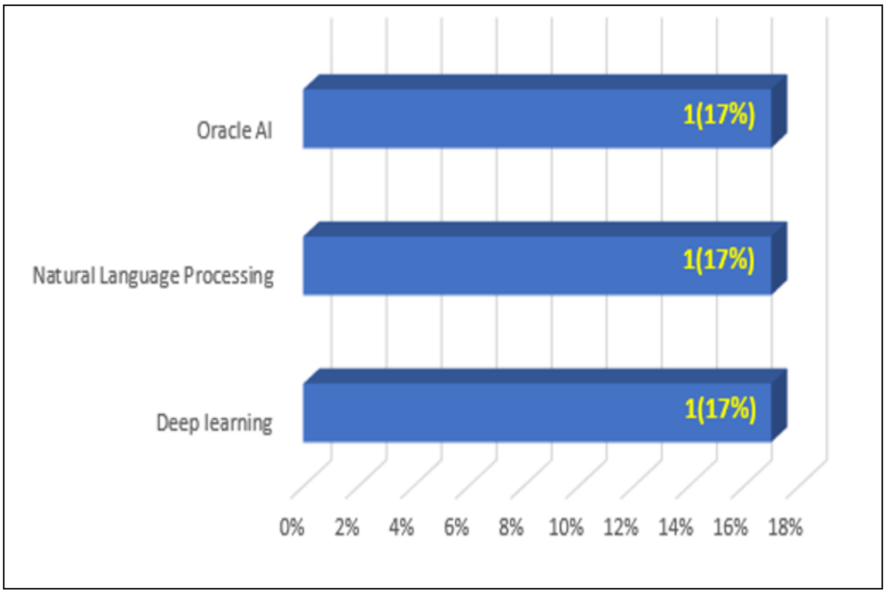

Figure 2: AI infrastructure used for records management (N = 6)

Participants responded that they knew about AI infrastructure such as automated classification that assists in classifying records captured by a robotic machine. Participants also responded that they were aware of automated rules and indicated that these rules could assist in controlling records and improving the accuracy and speed of meeting records requests.

Discussion of the findings

The discussion of this study is based on the study objectives.

Availability of electronic records management equipment

The availability of electronic resources indicates that an organisation is ready to apply and use AI for the management of records (Woordward, 2018). However, since CSIR has not yet adopted the application and use of AI for records management, there is equipment, such as robotic machine, that CSIR does not have. Yet the CSIR has most of the ICT resources that are required for records management using AI. All respondents indicated that CSIR had network coverage. CSIR uses networks for email and telephonic communication, among other things. This enables respondents to receive records requests and send records to users electronically. The majority of respondents (83%) indicated that CSIR had databases, a website and computer equipment, including printers and fax machines. This is the database that is used to retrieve and enable to store records on the local server. CSIR uses Micro Focus Vibe to store and retrieve records. CSIR uses its website to dissemintate information to users. All these resources would assist CSIR in migrating to AI for the management of records soon. None of the respondents indicated that CSIR required robotic machines to manage its records.

Rating the effectiveness of AI infrastructure in records management

AI infrastructure should be effective in the management of records. Effective AI infrastructure can ensure that records are managed effectively (Liu, 2011). The effectiveness of AI infrastructure will assist CSIR in ensuring that records are digitised, auto-classified, stored in the cloud, and quickly and easily accessed and retrieved. Hence, the majority of respondents (67%) agreed that AI infrastructure is effective for the storage of records. This might be because AI relies on cloud storage, which can store a large number of records securely. The majority of respondents (67%) also agreed that AI is effective for the maintenance of records. This might be because AI has the capacity to auto-classify records according to subject; records with similar subjects can therefore be stored together. 50% of the respondents agreed that AI infrastructure is effective in records classification, but only 33% agreed that AI infrastructure is effective in disposing of records. Respondents further indicated that AI does quality control during records creation and assist in reading data. Participants mentioned that AI infrastructure facilitates fast, accurate and reliable records management. They further responded that AI infrastructure provides high-quality metadata and accurate results that allow for effective records management.

AI infrastructure for records management

AI infrastructure plays a crucial role in ensuring that records are effectively managed (Keily and Hamm, 2013). AI facilitates automated classification, digitisation and cloud storage, and quick and easy access to and retrieval of records (Ripcord Company 2019). If CSIR wishes to manage its records effectively using AI, adequate AI infrastructure is required. The majority of respondents (67%) stated that they did not have knowledge of the AI infrastructure used to manage records. This might be because the respondents were not aware of the application and utilisation of AI for the management of records before a workshop facilitated by the researcher. 33% of respondents indicated that they were aware of AI infrastructure that could be used to manage records. Respondents had attended a workshop on the application of AI for records management before they completed the questionnaire, hence they were aware of AI for records management.

Participants responded that they knew that AI could be applied to records management, for example for the automated classification of records captured by a robotic machine. Participants also responded that they were aware of automated rules and indicated that these rules could assist in controlling records and improving the accuracy and speed of meeting records requests. A minority of respondents (17%) further stated that they were aware of deep learning and NLP as elements of AI that could be used for records management at CSIR. This might be because some of the respondents had read about the use of AI for records management. Deep learning uses a hierarchy of items, such as a classified file plan, to categorise content (Liu, 2011; Woordward, 2018). NLP is used to recognise concepts and metadata that are relevant to the file, as if an individual had physically read and selected concepts; it is therefore not only used to recognise concepts that occur regularly in a file (Melton & Hripsak, 2005). CSIR already has some knowledge of AI infrastructure required for effective and efficient records management at its disposal.

Recommendations

This section makes recommendations on AI infrastructure that could be used to manage records at CSIR.

Records management practitioners should familiarise themselves with the AI infrastructure used to manage digital records. Such AI infrastructure should accommodate deep learning, machine learning, robotic machines, NLP and automated classification algorithms. In addition, it should enable the secure and reliable retrieval, use, storage and disposal of the digital records. It is the responsibility of CSIR to ensure that it has the appropriate AI infrastructure for records management. CSIR should also ensure that records management practitioners are fully trained in using AI infrastructure and managing digital records.

This section further recommends a framework for the application of AI infrastructure for records management at CSIR. The framework aims to assist CSIR in managing its records effectively and efficiently using AI (including robotic machines, black boxes, and automated rules) that makes automated classification, machine learning, deep learning, the formation of neural networks and natural language processing possible.

Proposed framework

The study proposes a framework for the application of AI infrastructure for records management at CSIR (see Figure 3). The framework is based on AI, robotic models, and the records continuum, which are known for their ability to deal with the application of AI infrastructure for records management.

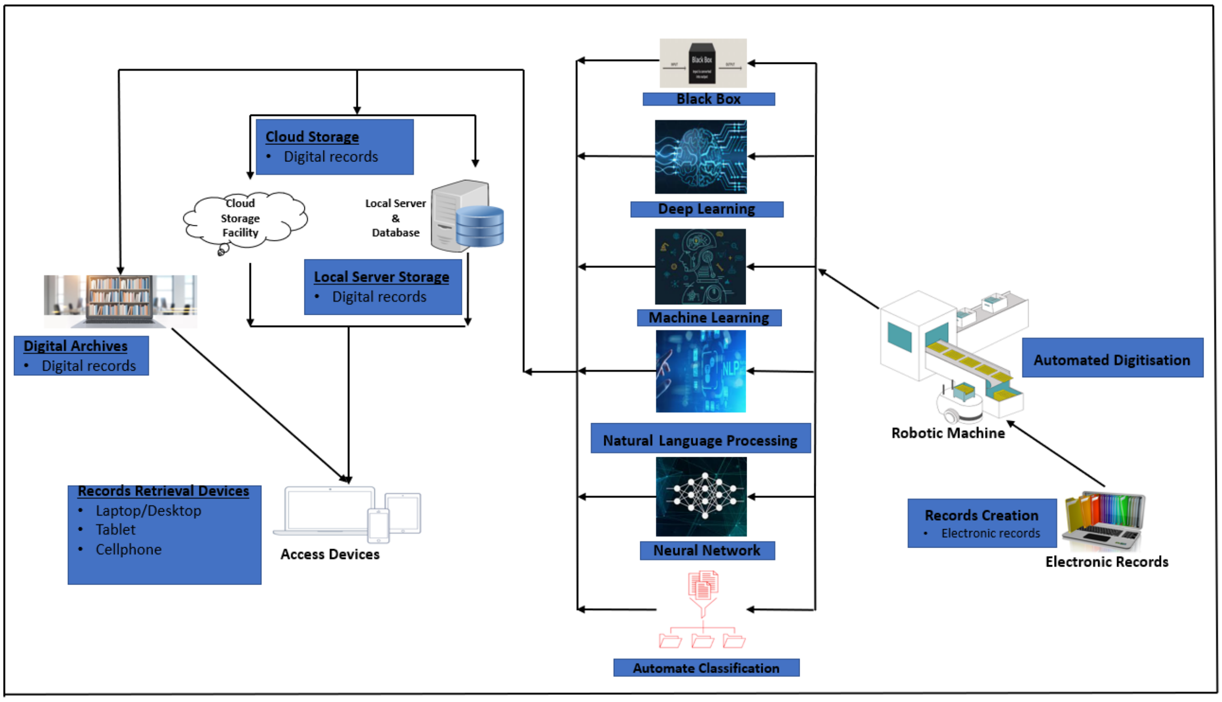

Figure 3: Framework for the application of AI infrastructure for records management

The framework starts with the creation of electronic records using computer technology. Such records include emails, MSWord documents and scanned paper-based records. Electronic records are then auto digitised by a robotic machine and the digital records are classified using an automated classification algorithm.

Neural network algorithms then ensure that the classification number of records are allocated before the digital records are transferred to the local server, cloud storage facility or digital archives.

NLP enables robotic machines to communicate with records management practitioners. Records management practitioners at CSIR will communicate with the robotic machine by either typing a request or sending a voice request. The robotic machine responds to requests in a pre-programmed manner; it can be programmed to answer both written and spoken requests. Machine learning algorithms enable robotic machines to update their databases automatically without being reprogrammed. Therefore, records management practitioners at CSIR will capture data once and the system will update on its own when new data are created.

Deep learning algorithms allow the computer brain to process even complicated tasks and learn from huge amounts of data. These algorithms also enable computers to analyse content and classify it correctly. Black box algorithms connect robotic machines and AI-empowered programs using input and output vectors. Smooth interaction and communication between systems are made possible by black box algorithms, therefore records can be retrieved and stored effectively and securely. Automated rules algorithms ensure that AI and robotic machines have set rules. Such set rules ensure for example that the system will automatically dispose of records at the correct time in line with CSIR file plan.

If records are auto classified and managed correctly using AI, such records can be retrieved using electronic devices like desktop computers, laptops, tablets and cellular telephones. Retrieved records can then be downloaded, saved, e-mailed to users and/or printed.

Conclusion

AI infrastructure embedded in robotic machines can be used to manage records at the CSIR effectively and efficiently. However, some records management practitioners at CSIR did not have knowledge of the AI infrastructure that would be required to manage CSIR's records. Some were aware of AI infrastructure used to manage records, but training and workshops should be designed to ensure that all records management practitioners become aware of AI infrastructure and how to apply it to records management. Records management practitioners at CSIR identified the following AI infrastructure: automated rules, deep learning and NLP. AI infrastructure can effectively be used to classify, store, maintain and dispose of digital records. AI infrastructure facilitates fast, accurate and reliable records management. It also provides the high-quality metadata and accurate results that effective records management requires. A framework for the application of AI infrastructure was proposed to illustrate how algorithms would interconnect to ensure there would be synergy between systems so that records could be managed effectively at CSIR.

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