A scoping review of literature on the application of swarm intelligence in the object classification domain

Nyaradzo Alice Tsedura (a)* Colin Chibaya (b) Ernest Bhero (c)

(a) School of Computer Engineering, University of KwaZulu-Natal, Durban, South Africa
(b) Doctor, Senior Lecturer, Computer Science, Data Science and Information Technology School of Natural and Applied Sciences, Sol Plaatje University, Kimberly, South Africa
(c) Doctor, Senior Lecturer, School of Engineering, University of KwaZulu-Natal, Durban, South Africa

ARTICLE INFO

Article history:
Received 03 May 2023
Received in rev. form 24 June 2023
Accepted 16 July 2023

Keywords:
object classification, swarm intelligence, emergent behaviour, scoping review

JEL Classification:
C89

ABSTRACT

This scoping review aims to explore the various swarm technologies and how they have been used in the object classification domain with the desire to motivate the design of a generic swarm intelligence ontology based on the components of various swarm technologies. We used the PRISMA-ScR as a guide to our scoping review protocol. We conducted a search across thirteen databases and a random search as well on the internet for articles. We performed screening of all the articles by title to remove duplicates, we further on did a screening by the year of publication to ensure that all articles to be considered were published between 2012 and 2022 and we then did abstract or text synthesis. Our search query retrieved 3224 potential articles from the thirteen databases and 10 articles from a random search on the internet making a total of 3234 articles identified. Deduplication and screening were done on the identified articles and 287 articles which satisfied our inclusion criteria remained. We grouped the articles into three categories namely year of publication, swarm technology and swarm application. The year of publication showed a linear trend line which is an indication of growth in the swarm intelligence domain. Of the six categories of aims we identified we voluntarily chose to ignore articles where the aim was not specified. We noticed that 64.9% of articles were aimed at either modifying or improving. The swarm technology category indicated that 58.54% of the included articles were based on the Particle Swarm Optimization either independently or as part of a hybrid algorithm. 83.97% of the articles used classification as their swarm application. Interesting to note was the appearance of feature selection and optimization in this category. This scoping review gave an overview of how swarm technologies have been used in the object classification domain. Further research can be done by bringing in and using existing algorithms in the development of generic swarm intelligence inspired ontologies.

Introduction

Object classification is important in areas such as computer vision (Kaur & Kaur, 2014; Lämmer et al., 2013), sensor-based security (Chowdhury et al., 2011; Sikder et al., 2021) and surveillance (Cucchiara, 2005; Micheloni et al., 2014), as well as in automated vehicle tracking (González et al., 2016; Jeevanantham et al., 2015) and parking systems (Hassoun et al., 2016; Revathi & Dhulipala, 2012). We contextually define the object classification problem as an attempt to identify and separate scene entities into different categories (Du et al., 2016; Mantini et al., 2021; Subba et al., 2019; Zeng et al., 2017). It is about assigning objects to pre-defined classes based on their features and attributes (Evans & Zhang, 2008b; Subba et al., 2019). Prevalently, machine learning models have largely been inferred for handling most objects classification problems (Bengio et al., 2013; Grendaitė & Stonèvichius, 2022; Gupta et al., 2021). Sufficient training data and robust statistical methods would be required to achieve quality and accurate object classification. However, access to such quality data for every object classification problem is an apparent challenge.

* Corresponding author. ORCID ID: 0009-0006-7836-2855
© 2023 by the authors. Hosting by SSBFNET. Peer review under responsibility of Center for Strategic Studies in Business and Finance.
https://doi.org/10.20525/ijrbs.v12i5.2586
Swarm intelligence is about exhibiting emergent behaviour from relatively simple naive and autonomous robotic devices interacting with one another in real time (Abraham et al., 2008; Chakraborty & Kar, 2017). It is that global intelligence of a swarm that summarizes the effect of the low-level actions of the individual robotic devices in the swarm.

The design of most swarm intelligence systems is prevalently nature inspired (Brezočnik et al., 2018; Chu et al., 2011), where individual robotic devices’ capabilities are limited but emulated from specific natural species. Although the actions of the individual swarm members are very basic, the swarm level emergent behaviour yielded is often complex (Chakraborty & Kar, 2017; Luque-Chang et al., 2018).

Many swarm intelligence technologies have been proposed for resolving real life object classification problems. Dominantly, the flocking behaviour (Bajec et al., 2007; Wagner & Cai, 2013) has been connoted for resolving the network routing (Wagner & Cai, 2013) problem. Also, variants of particle swarm optimization models (Evans & Zhang, 2008a; Perlin et al., 2008; Zemmal et al., 2020) have been visible in tackling various object classification problems, either directly or indirectly. In some cases, artificial bee colony models (Karaboga et al., 2014; Karaboga & Basturk, 2007) have been insinuated, together with ant colony optimization models (López-Ibáñez et al., 2018; Mahalingam & Subramoniam, 2020; Rao et al., 2017; Subba et al., 2019), schooling fish models (Lobato & Steffen, 2014), bacterial foraging optimization models (Chu et al., 2011; Lv et al., 2018; Zeng et al., 2017), and Social Spider Optimization models (Chandran et al., 2016; Evangeline & Abirami, 2019; Luque-Chang et al., 2018).

Although these numerous swarm intelligence technologies achieve fascinating simulated emergent behaviour using robotic devices with limited, if any, historic data, a formal investigation into what matters in the design of such robotic devices, why it matters, and how it matters, is lagging. For example, while the emergent behaviour exhibited in the creation of simulated beehives, ant hills, bird nests, or spider webs are compelling, what is in each robotic device that causes successful emergent behaviour? What comprise the knowledge domain of robotic devices in these swarm intelligence models?

This article seeks to understand the scope of literature on swarm intelligence which speaks to the key aspects of simulated swarms with which to infer solutions to the object classification problem. We seek to identify and characterize the various literature that closely dwelt on the object classification problems, scrutinizing the categories (Abraham et al., 2008; Chang et al., 2009) they emphasized, the contexts and methods embraced, their key variables and parameters of interest, as well as the main features of related swarms (Du et al., 2016; Rao et al., 2017). Hopefully, this would trigger generic swarm intelligence views applicable to the object classification problem. The proposed scoping review, in this case, is non-specific and general for any swarm intelligence-based object classification context. Key in this literature search is to seek an understanding of the commonly inferred insights. Knowledge of such insights may inspire successful determination of the key elements needed in the development of generic swarm intelligence ontologies. Such knowledge may also assist in the understanding of the likely verbs and the semantics of envisioned swarm coordination languages. We will also likely gain insights into what we can adopt when we want to tackle other broader practical problems where swarm intelligence views may suit. Importantly, the proposed scoping review may potentially take us closer to formalized swarm intelligence knowledge selection and representation.

The precise problem addressed by this scoping review is the identification of the scope of literature in the swarm intelligence domain which speaks to the object classification problem. We seek to identify literature which pinpoints the key swarm intelligence technologies useful in the object classification knowledge domain, as well as scrutinizing the elements of such swarm intelligence technologies that can motivate the design of generic swarm intelligence ontologies for resolving related problems. To achieve this, it is necessary to have a suitable literature search strategy, concise exclusion and inclusion criteria, and an appropriate articles screening approach.

An understanding of what matters when the topic on the application of swarm intelligence in object classification is tabled is the key aim of this study. We want to understand where, when, why and how such literature has been used. Also, we would want to elucidate the themes of most of such literature, as well as the key swarm control protocols they embrace.

Our three explicit objectives in this scoping review are, (a) to identify the relevant literature for the object classification within the swarm intelligence domain, (b) to characterize such literature, and (c) to analyze and categorize the literature that meet the inclusion criteria towards a broader picture of what matters, where, when, and how it matters in this domain?

The rest of the article proceeds as follows: section 2 shares the methods we followed in completing this scoping review. It starts by introducing the Population, Concepts, and Context (PCC) framework which guides the selection of the population of the articles to be included in the study, the key concepts to guide the scoping review, and the context in which these key concepts are applied. In this section we also emphasize the sources of the articles, the inclusion and exclusion criteria, as well as the article screening and reporting methods. The scoping review results are reported and analyzed in section 3, before we close the article in section 4, highlighting the striking conclusions, key contributions, and future direction of related studies.

**Research and Methodology**

It is vital to explain how the PCC framework guided this scoping review in identifying the suitable population of articles for the problem at hand. It is also strategic to discuss the sources of the articles considered in this scoping review, as well as fundamentally understanding the inclusion criteria which stipulate the article screening process. This section explicates on these aspects before we prescribe the reporting procedure that summarizes the evidence synthesis process thereto.
The PCC framework

The Joanna Briggs Institute (JBI) reviewer’s manual outlines a collection of mnemonics to suit diverse types of reviews (Peters et al., 2015). One of the mnemonics connoted is the PCC framework for scoping reviews (Peters et al., 2015). To develop the methods used in this scoping review, the PCC framework was used in identifying the population of relevant articles in the scope of swarm intelligence application in the object classification domain. The key concepts, and the context that informed the search strategy and the articles inclusion criteria are guided by the following question:

“What literature on swarm intelligence, where, when, why, and how, has it been inferred in resolving the object classification problem? What apparent gaps exist?”

We considered an open population of articles on swarm intelligence which connoted attempts to resolve the object classification problem. The key concepts of interest revolved around swarm intelligence application, swarm intelligence technologies, swarm intelligence elements, swarm intelligence languages, swarm intelligence modelling, and swarm coordination. These concepts were examined in the context of object classification. Our ambitious goal, throughout this study, remained the attempt to identify aspects of each identified swarm for consideration towards the development of generic swarm intelligence on technologies.

Sources of articles

A tedious literature search from thirteen online databases was undertaken to generate the population of relevant articles for this scoping review. These databases included the Cambridge Core, EBSCOhost, Emerald, ERIC, GreenFile, IEEE Xplore digital library, JSTOR, MasterFile Premier, ProQuest, ScienceDirect, Scopus, Springer, and Taylor & Francis. For literature currency, only those articles published between the years 2012 and 2022 were, inclusively, considered.

The JBI scoping review protocol (Bpharm et al., 2020; Peters et al., 2015) was adopted, where the population of articles with one or more of the following key concepts were nominated: swarm intelligence, object classification, swarm technology, swarm mechanism, swarm modelling, swarm language, swarm ontology. Papers whose context was on the application of swarm intelligence views in object classification were preferred. Only peer-reviewed conference and journal articles published in English were eligible. The deep inner focus of the studies was not of much relevancy to the inclusion of the article. Section 3 will discuss, in details, the articles mined from these databases.

Search strategy, inclusion, and exclusion criteria

To facilitate objective, consistent, and reproducible text mining from the databases, we developed a literature searching tool, here denoted as the LitSearchTool (). This LitSearchTool () exploited the identification of synonymous text that human would otherwise miss. Also, it took away the likely bias that would ensue when human typically select keywords based on their own understanding. The LitSearchTool () instigated reproducibility and consistency in the procedure followed during the literature search process. The snapshot below summarizes the query launched and committed through the execution of the LitSearchTool ().

```
DB <- <CambridgeCore|EBSCOhost|Emerald|ERIC|GreenFile|IEEEExplore|JSTOR|MasterFilePremier|ProQuest|ScienceDirect|Scopus| Springer|Taylor & Francis>
Concept <- <Swarm+<intelligence|technology|modelling|language|mechanism|ontology>
Context <- <object classification>

forEach db in DB
{
    population = population + SELECT * WHERE concept = TRUE AND context = TRUE
}
```

Databases were sequentially selected. In each case, articles that contained the key concepts, within the required context formed the population of relevant studies. The standard procedure to further verify the validity of the selected population of articles would be through manual screening, either by titles, abstracts, introduction, or by physically going through each entire article. However, we considered the use of a revtools R package that supports evidence synthesis through de-duplication of repeated articles. In using this revtools R package, we were guided by the PRISMA-ScR framework (Tricco et al., 2018) which facilitated the construction of a PRISMA flow diagram that shows the screening process, exclusions in each step, as well as the finally eligible articles.

Data extraction and collation

Articles that met the inclusion criteria were summarized in terms of the year of publication, their aim, the swarm intelligence technology embraced, the building blocks of the swarm language used, as well as the swarm application context. Figures, charts, and tables were the main reporting tools used to depict the knowledge maps arising from the eligible articles and the gaps thereof.
Results

This section summarizes our findings using a PRISMA-ScR diagram before the categories of the insights that ensued are discussed. Importantly, we pinpoint gaps in the literature that will likely inform further studies in the swarm-based object classification domain.

The PRISMA-ScR

Figure 1 illustrates the PRISMA-ScR diagram which indicates the flow of the article screening process we went through. Precisely, besides a search across the selected thirteen databases, a random search on the internet using the same search query and criteria specified in section 2.3 was also considered to, merely, exhaust possibilities of leaving out some eligible articles. A total of 3234 articles, combined, we identified as meeting the PCC framework. An SQL query was developed to augment the revtools package in screening these articles. A total of 424 articles were excluded from the population after the first screening round because they were duplicates. In this case, some articles had the same title, same authors, or they were published in the same year by the same people on the same subject. Listing 1 illustrates the SQL query for this de-duplication process. Notably, some of these articles were possibly duplicated because they were saved in several online databases.

Listing 1: Query extracted from revtools R package; Source: Authors

```
select * from (
    select row_number() over (partition by Title, Author, Year),
    title,
    author,
    year
    from ScopingReview)
t
where t.row_number < 2;
```

Figure 1: PRISMA-ScR Diagram; Source: Authors
The second round of screening involved scrutinizing the content of the remaining articles whose titles sounded close. The same revtools R package successfully picked 9 articles with titles that slightly differed when, in fact, the content of the articles reported the same research. Subsequently, another 4 articles were discarded by text synthesis where, although the titles differed, the abstracts pointed to the same research. The last chunk of 101 articles fell off because they were published before the year 2012. About 2408 articles remained valid after this second round.

The third round dropped the prime portion of the population. In this case, articles were discarded because, either they were not within the context of swarm intelligence application within the object classification domain, or the swarm technology embraced was not specified. Some fell off because the methods inferred were not necessarily within the swarm intelligence domain. After this critical round, 287 articles remained eligible and were considered for further analyzes in the rest of this scoping review.

Categories of eligible articles

The 287 articles that remained eligible within the scope of this review in the context of the concept of swarm intelligence-based object classification were scrutinized and grouped into four categories. We firstly checked the distribution of these articles by year of publication. Then, the main aims and the focuses of these articles were also of interest. In addition, we also looked at the distribution of these articles by the swarm technology each eligible article embraced. Lastly, we categorized these included articles by the swarm application connoted in the study. The remainder of this section presents the results yielded in each category.

Distribution of the included articles by year of publication

Part of the inclusion criteria was to consider articles that were published from the year 2012 to the year 2022. Scrutinizing the distribution of the included articles by year allows us to see research growth patterns in the swarm intelligence domain’s application in the field of object classification. Figure 2 shows the distribution of the 287 included articles by year. Fitting a linear trend line in the yielded frequency distribution shows that, generally, research in this knowledge domain has been steadily growing over the years. The drop observed in the number of articles published in the year 2022 is, probably, because some articles were still under reviews for publication considerations at the time of completing this study. Similarly, that drop noted in the year 2020 could, probably, be attributed to the effects of the COVID-19 pandemics worldwide. However, generally, the observed growth in interest by researcher in undertaking studies on this topic justifies the worthiness of this study. Interests in any further investigations inferred as upcoming after this scoping review are vindicated as bona fide towards addressing a popular agenda. Our desire to join this growing area of research towards understanding swarm intelligence systems for resolving the object classification problem is, therefore, a niche avenue to pursue further in upcoming studies.

![Figure 2: Included articles distribution by year of publication; Source: Authors](Figure 2)

Distribution of articles by year of publication

Distribution of the included articles by aim

In the context of this study, an aim is an intention, goal, focus, or the objective driving the research. Five categories of the aims of most swarm intelligence articles were identified in the scoping review as (a) to compare swarm intelligence models, (b) to evaluate functionalities of swarm intelligence systems, (c) to improve swarm intelligence models, (d) to investigate how swarm intelligence models work, or (e) to modify some swarm intelligence algorithm for one reason or another. However, there were circumstances where aims were not explicitly given. There are situations where such aims were difficult and too implicit to categorize. Figure 3 shows the distribution of the aims picked in the included articles.

![Figure 3: Distribution of the included articles by aim; Source: Authors](Figure 3)
Dominant were articles that did not pinpoint the aim. However, the bigger picture observed from the study points to the popularity of articles that emphasize modification and improvement of known swarm intelligence models. Generally, most research focused on solving discrete problems where generality is not of concern. Thus, one swarm intelligence model could be modified into differently variants depending on the area of application sought. Of interest to us is that studies aimed at finding ways to re-use known swarm intelligence technologies in solving real life problems are, thus, apparently popular. In fact, modification, or improvement of particular swarm intelligence views towards generality is a worthwhile avenue of research to pursue.

![Diagram: Distribution of articles by aim]

**Figure 3:** Distribution of Included articles by aim, *Source: Authors*

**Distribution of the included articles by swarm technology**

Swarm technology refers to the inspiring natural self-organized systems (Yu et al., 2021). For example, there are swarm intelligence systems whose swarm technologies are ant colonies, fish schools, bee swarms, social spider swarms, or flocking birds. The goal is to see the popularity of each swarm technology in the resolution of the object classification problem. Potentially, that knowledge will give useful insights into what works best for the problem at hand and why so.

Table 1 summarizes the swarm technologies that were prevalently used in the included articles. Twenty-one combinations of these swarm technologies were observed from the included articles. In some instances, non-swarm intelligence technologies, such as Support Vector Machines and Convolutional Neural Networks, were combined with swarm intelligence view to improve swarm performance. However, the dominance of Particle Swarm Optimization (PSO) in solving most object classification problems is compelling. This ignites questions such as (a) Is this dominance of PSO because of the properties and the component units of this swarm technology? What is in the PSO swarm technology that causes related emergent behaviour to arise? What is missing in other swarm technologies that is found in PSO models? Notable in this scoping review is that further research may ensue which investigate all these questions from different perspectives. Additionally, it may be worthwhile to pursue an understanding of what matters in PSO models that give rise to emergent behaviour. Also, one could experimentally assess if it is impossible to achieve what PSO models achieve using other swarm technologies.

Artificial bee swarm technology is also notably popular. Similar questions can be asked. More importantly, any resemblance between artificial bees and PSO may give insights towards those important swarm aspects we seek towards generality. Further studies to investigate such resemblances is another apparent gap this scoping review unearthed.
Table 1: Distribution of Included articles by swarm technology

<table>
<thead>
<tr>
<th>Swarm Technology</th>
<th>Number of articles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beetle Swarm Algorithm</td>
<td>1</td>
</tr>
<tr>
<td>Bird Swarm Algorithm</td>
<td>2</td>
</tr>
<tr>
<td>Chicken Swarm Optimization</td>
<td>2</td>
</tr>
<tr>
<td>Crow Search Algorithm</td>
<td>1</td>
</tr>
<tr>
<td>Cuckoo Search Algorithm</td>
<td>3</td>
</tr>
<tr>
<td>Grey Wolf Optimization</td>
<td>1</td>
</tr>
<tr>
<td>Monkey Search Algorithm</td>
<td>1</td>
</tr>
<tr>
<td>Not Specified</td>
<td>87</td>
</tr>
<tr>
<td>Salp Swarm Algorithm</td>
<td>2</td>
</tr>
<tr>
<td>Particle Swarm Optimization</td>
<td>162</td>
</tr>
<tr>
<td>Artificial Bee Colony</td>
<td>10</td>
</tr>
<tr>
<td>Swarm Intelligence, Chaos</td>
<td>1</td>
</tr>
<tr>
<td>Artificial Fish Swarm</td>
<td>1</td>
</tr>
<tr>
<td>Artificial Bee Colony, Particle Swarm Optimization</td>
<td>1</td>
</tr>
<tr>
<td>Particle Swarm Optimization, Support Vector Machine</td>
<td>4</td>
</tr>
<tr>
<td>Artificial Bee Colony, Support Vector Machine</td>
<td>1</td>
</tr>
<tr>
<td>Ant Colony Optimization</td>
<td>5</td>
</tr>
<tr>
<td>Particle Swarm Optimization, Artificial Neural Network</td>
<td>1</td>
</tr>
<tr>
<td>Swarm Intelligence, Support Vector Machine</td>
<td>1</td>
</tr>
</tbody>
</table>

Source: Authors

Distribution of the included articles by swarm application

Swarm application denotes the problem a swarm intelligence system solved. Although swarm intelligence systems predominantly dwell on resolving the scheduling, classification, prediction, feature selection, optimization, or image segmentation problems, the search query we used in this study emphasized the object classification problem. Hence, most included articles were on classification, feature selection, and a combination of classification and optimization. Figure 4 shows the distribution of these articles by swarm application.

The finding that about 83.97% of the included articles were grounded on resolving the classification problem validates the search query we used. Although a few other articles pondered on feature selection, it is compelling to discover that feature selection is, in fact, a classification task. This finding is appealing in two ways. Does the classification problem insinuate the dominance of PSO swarm technology? Would other swarm applications insinuate different swarm technologies? These questions are, also, some of the deliverables of this scoping review that may trigger the need to modify, improve, and generalize particular swarm intelligence algorithms for real life solutions.
The next section abstractly shares the key observations that emanated from the study before we draw the conclusion, contributions, and point to the direction for future work.

Conclusions

We pose several reflections from the results yielded from this study. The requirement for progression in the subject of swarm intelligence-based object classification is evidently visible from the observed growth in attention over the years. Improvement and modification of existing swarm intelligence models will likely provide the breakthrough towards generalization. Also, it is compelling to note that different swarm technologies seem best applicable to different problem domains, and PSO looks quite popular in the object classification space.

Three main observations stand out from this study as follows:

i. A few questions are unanswered. In this case, what really defines a PSO model which results in successful object classification? What is it that is missing in other models to result in this form of emergent behaviour? Further research to answer these questions is upcoming.

ii. We also observe that feature selection is, in fact, a classification problem. What relationship could possibly be between feature selection and PSO? What relationships exist between feature selection and object classification? Further studies to clarify these questions is required.

iii. Although there are articles that connoted involvement of swarm intelligence in the field of object classification, there are no formal knowledge representation models in place to explain how such solutions are derived. There is a lack of formal swarm intelligence ontologies for this purpose. The design and formalization of swarm intelligence ontologies for object classification is a clear avenue of research to explore further in this area.

Two apparent gaps can, therefore, be isolated from this study as follows:

i. While there is evident growth in the use of swarm related technologies to solve the object classification problem, where are we really going? What do we want to achieve? An understanding of the ultimate hope of swarm intelligence in this knowledge domain is key. In our view, arrival at a generalized formal swarm intelligence ontology for this knowledge space is the destination thereto.

ii. Although we observed that prevalently, most studies seek to improve or modify existing swarm intelligence algorithms, which models perform best in particular contexts? Thorough comparative studies, rigorous evaluations, and deep investigations of the key details of these existing swarm intelligence models is essential? A deep understanding of those algorithms already in place is important. Thereafter, work on improving these algorithms will, hopefully be far much easier.

The visible contributions of this scoping review are twofold:

i. The scoping review elucidated apparent imbalances in the distribution of the articles published in the swarm intelligence-based object classification domain. First, there is an imbalance in the aims of most articles. There also a clear bias in the swarm technologies inferred. This discovery is an opportunity for further engagements and deep research in the field. Our scoping review cleared a baseline pathway upon which further innovative research may be built on.
This study presented substantial educational angles of research in the field which new entrants in the field can exploit. This scoping reviews may be a good starting point in tackling these angles.

Four directions for future work are likely as follows:

i. We hope to explicitly understand the grounding factors of particular swarm intelligence technologies which cause deterministic emergent behaviour, in this case, object classification.

ii. A comprehensive understanding of the building blocks of particular swarm technologies is justified by the scope of existing literature which talks to biased use of the PSO for the object classification problem. Precisely, what does other swarm technologies offer? Why are they silent when the object classification problem is tackled?

Hopefully, an understanding of what matters in each case, why it matters, how so, and when it is important to consider each swarm technology will propel the swarm intelligence agenda in problem-solving.

Acknowledgments

We acknowledge both the moral and technical support given by the University of KwaZulu-Natal and the Sol Plaatje University. We also acknowledge the CAIR project: grant agreement number: CSIR/BEI/HNP/CAIR/2020/10, supported by the Government of the Republic of South Africa, through its Department of Science and Innovation (DSI).

All authors have read and agreed to the published version of the manuscript. 

Author Contributions: Conceptualization, Alice Nyaradzo Tsedura, Colin Chibaya, and Ernest Bhero; Methods, Alice Nyaradzo Tsedura and Colin Chibaya; Investigation, Alice Nyaradzo Tsedura and Colin Chibaya; Formal analysis, Alice Nyaradzo Tsedura; Data curation, Alice Nyaradzo Tsedura; Writing—original draft preparation, Alice Nyaradzo Tsedura; Writing—review and editing, Alice Nyaradzo Tsedura, Colin Chibaya and Ernest Bhero; Supervision, Ernest Bhero and Colin Chibaya; Project administration, Ernest Bhero and Colin Chibaya; Funding acquisition, Ernest Bhero and Colin Chibaya. Authorship has been limited to those who have contributed substantially to the work reported.

Funding: This work was undertaken within the context of the Centre for Artificial Intelligence Research that is supported by the Centre for Scientific and Innovation Research (CSIR): grant number: CSIR/BEI/HNP/CAIR/2020/10, supported by the Government of the Republic of South Africa, through its Department of Science and Innovation’s University Capacity Development grants.

Informed Consent Statement: All authors have read and agreed to the published version of the manuscript. All authors have consented to the publication of this manuscript.

Data Availability Statement: All the data supporting the reported results is included in the manuscript. Additional materials are provided in a separate excel file.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of the data; in the writing of the manuscript; or in the decision to publish the results. There are no competing interests for this study. The authors declare no conflict of interest.

References


**Publisher’s Note:** SSBFNET stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

© 2023 by the authors. Licensee SSBFNET, Istanbul, Turkey. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

International Journal of Research in Business and Social Science (2147-4478) by SSBFNET is licensed under a Creative Commons Attribution 4.0 International License.