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Sirmayanti [1*], *Pulung Hendro PRASTYO* [1], *Mahyati* [1], *Farhan RAHMAN* [1]
[1] Politeknik Negeri Ujung Pandang, Indonesia, sirmayanti.sirmayanti@poliupg.ac.id, pulung.hendro@poliupg.ac.id, mahyatikimia@poliupg.ac.id, farhanrahman@poliupg.ac.id
[*] Corresponding author: sirmayanti.sirmayanti@poliupg.ac.id

A systematic literature review of diabetes prediction using metaheuristic algorithm-based feature selection: Algorithms and challenges method

Abstract

Diabetes is a disruption in metabolism that leads to elevated levels of glucose in the bloodstream and causes many other problems, such as stroke, kidney failure, heart, and nerve issues that are of serious concern globally. Because many researchers have attempted to build accurate Diabetes prediction models, this field has seen significant advancements. Nevertheless, performance issues are still a substantial challenge in model building. Machine Learning techniques have shown strong performance in prediction and classification tasks. Unfortunately, they often encounter challenges due to noisy features and high feature space dimensionality, significantly affecting Diabetes prediction performance. To address the problems, we can employ metaheuristic algorithm-based feature selection. However, there has been limited research on metaheuristic algorithm-based feature selections for Diabetes prediction. Therefore, this paper presents a systematic literature review of Diabetes prediction using metaheuristic algorithm-based feature selections. The data used in this study is the last ten years of published articles from 2014 to 2024. For this extensive investigation, 50 scholarly papers were gathered and analyzed to extract meaningful information about metaheuristic algorithm-based feature selections. This paper reviews metaheuristic algorithm-based feature selection, focusing on the algorithms used and the challenges faced in diabetes prediction.

1. INTRODUCTION

Diabetes and some of its derivatives, such as Diabetes Mellitus (DM) Type-1 and Type-2 are chronic metabolic disorders in the human body. Diabetes is generally known as a disease that has a high risk of death and has raised many threats in the world, especially in Indonesia. The International Diabetes Federation (IDF) reported that in 2022, the number of patients with type 1 Diabetes in Indonesia was 41.8 thousand. This number has made Indonesia the country with the most Type 1 Diabetes patients in ASEAN, as well as 34th out of 204 countries on a global scale. Diabetes prediction is usually done through medical examination by competent health professionals (Shuja et al., 2018).

The application of Artificial Intelligence (AI) and Machine Learning (ML) in healthcare is revolutionizing the field by improving disease diagnosis, treatment, and overall patient care efficiency. AI systems can analyze extensive clinical data to deliver precise diagnoses and tailor treatment plans, leading to better healthcare outcomes (Chui et al., 2023). ML allows computers to learn from data and execute specific tasks, such as classifying diseases like Diabetes through pattern recognition (Lukmanto et al., 2019). However, challenges such as high dimensionality and noise in the data can impact the performance of algorithms, highlighting the need for effective feature selection methods (Qaraad et al., 2021).

Feature selection is a key dimensionality reduction technique that identifies the most relevant features while eliminating noise, thereby improving the performance of ML algorithms and reducing computation time (Abdel-Fattah Sayed et al., 2016). Feature selection is commonly used as a preprocessing technique in ML to improve learning performance and overcome problems associated with high-dimensional datasets (Tarik et al., 2023). In high-dimensional datasets, reducing dimensionality is essential to prevent overfitting, enhance interpretability, and improve model efficiency (Sameen Hameed et al., 2018). Non-essential features can reduce the accuracy of classification outcomes and complicate the task of extracting meaningful insights from the data (Bielza & Larrañaga, 2020). Dimensionality reduction methods can be categorized into feature selection and feature extraction. While feature selection retains original variables by selecting the most relevant ones, feature extraction transforms the dataset into a lower-dimensional space while preserving critical information (Jia et al., 2022). Common feature extraction techniques include Principal Component Analysis (PCA), which projects data onto orthogonal components maximizing variance, and Linear Discriminant Analysis (LDA), which optimizes class separability (Karpiński et al., 2022a). Feature selection methods play a crucial role in healthcare technology systems, where high-dimensional biomedical data must be efficiently processed for accurate diagnostics and decision-making (Karpiński et al., 2022b).

Feature selection approaches can be broadly classified into Filter, Wrapper, and Embedded methods. Filter methods rank features based on statistical metrics such as correlation coefficients or mutual information, making them computationally efficient but independent of ML models (P. Agrawal et al., 2021). In contrast to the Filter method, the Wrapper method combines metaheuristic algorithms with ML algorithms to obtain the best features and gives better results than the Filter method. This approach is based on a modelling algorithm that generates and evaluates each subset. The generated subset in Wrapper techniques is derived from various search algorithms (Le et al., 2021). Meanwhile, the Embedded method efficiently selects features and performs well in the training process (Liu et al., 2020). The hierarchy of feature selection algorithms can be seen in Fig.1.

Considering the Wrapper methods, there are three search technique modes: Exponential, Sequential, and Randomized selection strategies. In the Exponential method, the evaluated features will continue to increase exponentially making it unstable for situations with limited resources (Perveen et al., 2016). Then, the Sequential algorithms include or remove features sequentially. Randomized algorithms use random techniques to explore the search space, preventing the algorithm from getting stuck in the local optima. Randomized algorithms are population-based approaches, such as simulated annealing, random generation, and metaheuristic algorithms (Akinola et al., 2022).

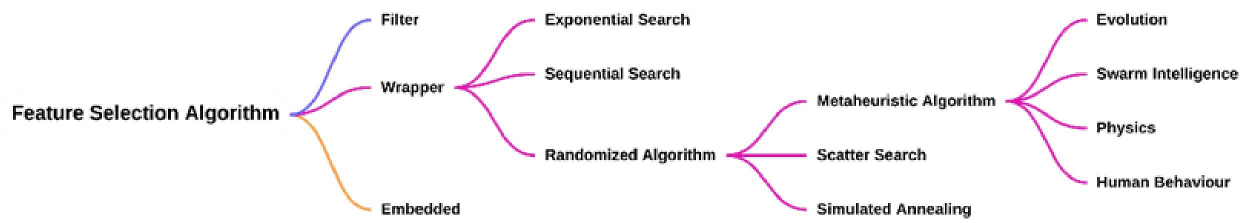

Fig. 1. The hierarchy of feature selection algorithms (P. Agrawal et al., 2021)

The metaheuristic algorithm, the main review of this study, is an optimization method and a derivative-free technique that obtains the optimal solution to an optimization problem and also can avoid local optima (Mirjalili et al., 2014). Metaheuristic algorithms operate stochastically, initiating the optimization by generating multiple random solutions rather than using gradient-based methods to calculate derivatives of the search space (P. Agrawal et al., 2021). These algorithms are known for their flexibility and simplicity, owing to their straightforward concept and ease of implementation. This concept makes the technique a "black box" as it is not always clear how the algorithm makes the decision (Tomar et al., 2023). This has the advantage of avoiding local optimization when exploring the search space.

Metaheuristic algorithms receive substantial scholarly attention due to their distinctive characteristics. Numerous algorithms have been developed for various problems. There are four groups of metaheuristic algorithm behavior: Evolution, Swarm Intelligence, Physics, and Human Behavior. Firstly, Evolution-based algorithms are inspired by natural evolution and begin with a randomly formed population. In this algorithm, the best solutions are combined to generate new individuals. Mutation, crossover, and selecting the optimal solution contribute to produce new individuals (P. Agrawal et al., 2021). Secondly, Swarm Intelligence-based algorithms are inspired by the social behavior of insects, animals, fish, birds, etc. A popular technique is Particle Swarm Optimization developed by Kennedy and Eberhart (1995). Thirdly, Physics-based algorithms refer to computational methods that utilize principles of physics to solve problems such as Newton's laws of motion, Maxwell's equations, thermodynamics, and others. By incorporating these physical principles into computational models, physics-based algorithms aim to simulate and predict the behavior of real-world systems (Alatas & Can, 2015). Lastly, human-related algorithms are designed to process or analyze data related to human activities, behaviors, or characteristics (Donahue et al., 2022).

Research on Diabetes prediction highlights the importance of feature selection for improving classification accuracy and reducing computational complexity. Metaheuristic algorithms have shown promise in optimizing this process by effectively navigating large datasets to identify relevant features. Despite their potential, there is a lack of comprehensive studies reviewing the use of these algorithms for feature selection in Diabetes cases, including their types, implications, and challenges. This study aims to fill that gap by providing a systematic literature review. The paper is organized as follows: Section 2 details the research methodology, Section 3 presents the main findings, Section 4 discusses these results in depth, and Section 5 concludes the study.

2. METHOD

2.1. Review method

The Systematic Literature Review (SLR) method emphasizes the case of Diabetes prediction using a metaheuristic-based feature selection method. SLR identifies, assesses, and interprets all related research to answer specific research questions (Kitchenham et al., 2009). The significance of this study lies in the comprehensive analysis of diverse metaheuristic algorithms and the associated challenges encountered in the prediction of Diabetes. Thus, the effectiveness and efficiency of the method in identifying the problems can be understood.

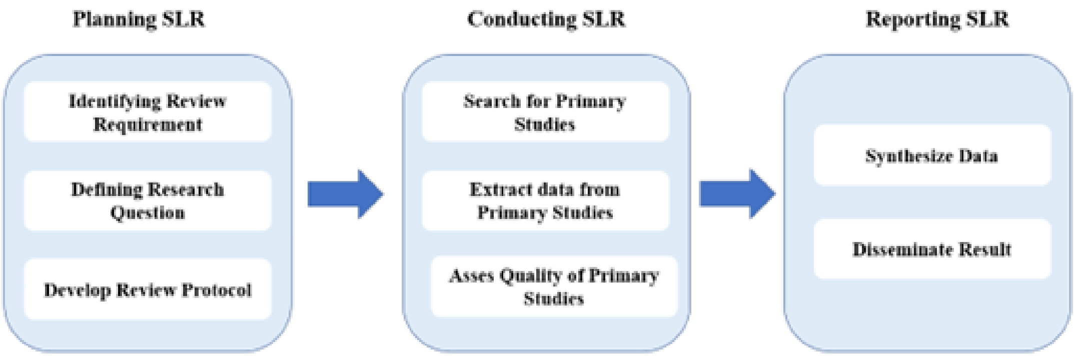

Fig. 2. The SLR process

In Fig. 2, the SLR process is carried out in 3 stages: Planning, Conducting, and Reporting. The Planning initially involves identifying requirements for the SLR. Next, research questions are defined to enhance the purpose of conducting SLR. Then, developing review protocol through planning to reduce the possibility of researcher bias. The developed review protocols define clear and well-defined research questions, ensure the research question is relevant to the field of study and has practical implications as well as determine the objectives of the review. Then, the Conducting SLR stage begins to search for primary studies by entering keywords to look for relevant papers. After that, the information is gathered from primary studies to compile papers for analysis. Next, we evaluate the quality of primary studies based on the collected information. The final stage involves reporting the SLR findings by synthesizing data and documenting the analysis results.

2.2. Research questions (RQ)

The RQ are given to find answers to the research. In addition, research questions are made to sharpen the research so that it can find novelty in all research results later.

Tab. 1. Research questions and motivations

ID	Research Question	Motivation
RQ1	What are the most commonly used Metaheuristic Algorithms?	To identify the types of metaheuristic algorithms frequently used in various papers for feature selection in the case of Diabetes prediction.
RQ2	What types of datasets are often used by researchers related to Diabetes prediction using metaheuristic algorithms?	To find out what datasets are used by the papers
RQ3	What are the best-performing metaheuristic algorithms?	To find out the best metaheuristic algorithm applied.
RQ4	Where have the paper articles related to Diabetes prediction using metaheuristic algorithms been published?	To understand the search strategy for journals and articles on metaheuristic algorithm research.
RQ5	What are the challenges experienced in each article when applying metaheuristic algorithms?	To find out the challenges experienced regarding metaheuristic algorithm research.

These questions in Tab. 1. are the objectives of this SLR. RQ1 is answered from the analysis results on what metaheuristic algorithms are often used in Diabetes prediction. Then, RQ2 is answered by identifying the dataset the paper uses in its experiments. After that, This SLR also answers RQ3 related to the metaheuristic algorithms that have the best performance. Furthermore, this SLR also identifies paper publications related to the utilization of metaheuristic algorithms in Diabetes prediction in RQ4. Lastly, RQ5 aims to analyze the research challenges

2.3. Search strategy

This SLR study technique to examine research trends during the last ten years, 2014–2024. To ensure extensive coverage of pertinent literature, this study incorporated several prominent scientific databases, including PubMed, Scopus, and OpenAlex. In addition, we use academic search engines like Google Scholar and Semantic Scholar to acquire access to a wide range of intellectual resources, such as journal articles, theses, books, and conference papers. Using these various databases and search engines gave us the advantage of collecting comprehensive and representative literature from multiple disciplines. As such, we were able to ensure that our review covered a diverse range of perspectives and current findings within our field.

2.4. Search keyword

In this study, keywords were meticulously extracted from the titles, abstracts, and keywords of relevant articles to ensure comprehensive coverage of the literature. By employing a combination of specific and interchangeable keywords, would direct to cast a wide net and capture diverse perspectives on the intersection of metaheuristic algorithms and Diabetes prediction. These keywords include terms such as "Metaheuristic Algorithm," "Diabetes Disease," and "Disease Detection," among others, which were carefully chosen to encompass various aspects of the research domain. Additionally, synonymous terms and related concepts such as "Machine Learning," "Optimization Algorithm," and "Feature Selection" were incorporated to broaden the scope of the search and uncover additional relevant research articles. This systematic approach to keyword selection enhances the efficiency of the literature review process. It ensures that no relevant studies are overlooked, ultimately contributing to a comprehensive topic analysis.

2.5. Inclusion and exclusion criteria

In this SLR, the inclusion and exclusion criteria are used to identify all relevant studies as well as shown in Tab. 2. This SLR will comprehensively focus on using metaheuristic algorithms to perform feature selection and extraction in detecting Diabetes and will be included in the inclusion criteria. To ensure focus, studies that do not provide answers to the research questions or explore a different area will be omitted from this review.

Tab. 2. Inclusion and exclusion criteria involved in the search process

Inclusion	Exclusion
Using English and Bahasa Indonesia	Research subjects have no relevance to the research question.
Research that discusses the application of metaheuristic algorithms as feature selection for prediction cases of Diabetes	Research that is not full-text articles
Research equivalent to qualifications Q1, Q2, Q3, Q4	Research with non-academic databases

2.6. Data collection

The selected papers were then collected to answer the research question in this review. The data used in this study is the last ten years of published articles from 2014 to 2024. The data collected in the research are source (journal or conference), summary that includes the essence of the research question and answers, type of dataset used by the paper, type of metaheuristic algorithms applied in the research and recommendations by the authors, and place of publication of the paper. After gathering the information, it will be consolidated and evaluated to offer a complete picture of how various studies have handled the research issue, their methodology, and any common topics or recommendations that emerge from the literature. This synthesis serves as the foundation for the review, providing readers with an understanding of the current level of research on the subject.

3. RESULTS

Data collection of metaheuristic algorithms and their performances:

Tab. 3a. Search results of metaheuristics algorithm-based on grey wolf optimization (GWO) usage and their performance

Authors	Dataset	Performance result
(Le et al., 2021)	ES	The proposed method obtained 97%
(Shankar & Manikandan, 2019)	PIMA	The algorithm optimizes the local features only and gives 71% accuracy
(Bilal et al., 2022)	DIARETDB	The classification accuracy is 98.33%
(Mallika & Selvamuthukumaran, 2021)	PIMA	The method reached accuracy rate of 89%

Tab. 3b. Search results of metaheuristics algorithm-based on particle swarm optimization (PSO) usage and their performances

Authors	Dataset	Performance result
(Karthikeyan & Alli, 2018)	OCT	SVM with Hybrid GWO-PSO feature selection and parameter optimization got an accuracy of 97%
(Chellappan & Rajaguru, 2023a)	Microarray Gene	Accuracy of proposed method achieved 91%
(Navazi et al., 2023)	ES	PSO-GA-SVM got 93% Accuracy
(Abdollahi & Aref, 2024)	AIM'94	DT, RF and NB got the highest accuracy and lower error

Tab. 3c. Search results of metaheuristics algorithm-based on genetic algorithm (GA) usage and their performances

Authors	Dataset	Performance result
(X. Li et al., 2023)	PIMA & ISD	GA-KNN got 68% accuracy in PIMA and 95% accuracy in ISD
(García-Domínguez et al., 2023)	Custom 1	The proposed model surpassed accuracy of 94%
(Abdollahi & Nourimoghaddam, 2023)	130-US	GA reached 85.61% as the highest accuracy
(Ullah et al., 2022)	KDR & Custom	The proposed method obtained 97.9% of accuracy
(Gupta et al., 2022)	ES	The method got classification results accuracy of 98.86%
(Welikala et al., 2015)	MESSIDOR	The model achieved sensitivity of 91%
(Al-Tawil et al., 2023)	PIMA & HFD	GA-LR obtained 80% of accuracy
(Vaishali et al., 2017)	PIMA	MOE NSGA II fuzzy obtained an accuracy of 83.04%

Tab. 3d. Search results of metaheuristics algorithm-based on whale optimization algorithm (WOA) usage and their performances

Authors	Dataset	Performance result
(Astuti et al., 2022)	PIMA	WOA-NN got 75% of accuracy
(Hoda & Nadimi-Shahraki, 2016)	PIMA	Proposed algorithm observed on PIMA : 78.57%

Tab. 3e. Search results of metaheuristics algorithm-based on bat algorithm (BA) usage and their performances

Authors	Dataset	Performance result
(Soliman & Elhamd, 2015)	PIMA	The proposed method got an accuracy of 98.65%
(Yasaswini & Baskaran, 2021)	PIMA	MBA achieves 79.81% Accuracy
(Abdullah et al., 2018)	MESSIDOR, DRIVE, DIARETDB1, DIARETDB0, STARE, DRIONS	The proposed algorithm got accuracy of 96%
(Jain & Singhal, 2023)	PIMA	BA performs better with 97% accuracy

Tab. 3f. Search results of other metaheuristics algorithm-based usage and their performances

Authors	MA	Dataset	Performance result
(Jadhav et al., 2021)	ROA	DIARETDB1	The method reached 93% Accuracy
(Reddy & Khare, 2017)	FFA	PIMA	FFA attains 79% as the best performance and 70% as the worst performance
(Patil et al., 2022)	MOA	PIMA	MOA attained max test accuracy of 95.5% over PIMA
(Patil et al., 2020)	ACO	PIMA	ACO observed that accuracy had been 86.27%
(Chellappan & Rajaguru, 2023b)	HOA	Microarray Gene	EHO of AAA with SVM(RBF) exhibited the highest accuracy of 95.714%,
(Hartono, 2022)	MOBA	PIMA	MOBA-NB classification accuracy was 77,5%
(Chaudhuri & Sahu, 2021)	BCSA	PIMA	BCSA Reached 86.66% Accuracy
(Gadekallu & Khare, 2017)	CS	Custom 2	CS-Rough Set Theory got accuracy 89,5%
(J. Li et al., 2022)	MMA	Custom 3	The model obtained 95% of accuracy
(Dehkordi et al., 2019)	WWOA	PIMA	Accuracy of 95.46%, and was more sensitive than the methods
(Nagaraj et al., 2021)	AFA	Custom 4 & 130-US	The accuracy of the 130-US dataset is 99,88%.
(Kamel & Yaghoubzadeh, 2021)	GO	PIMA	The study result has shown a promising accuracy of 97% with GO-SVM
(Sravanthi et al., 2023)	BGW-CSO	PIMA	BGW-CSO-SVM approach outperforms with a remarkable accuracy of 96.62%
(Sutha et al., 2023)	HYBPFO	PIMA	HYBPFO-Sel_Stack_AdaCat obtained 98.7% of accuracy
(Sun et al., 2022)	SCA	PIMA	Diabetes data with METASCA achieved accuracy of 78%
(Zhang et al., 2024)	HS	PIMA and CWMD	The method got better accuracy than all benchmark model
(Kulkarni & Deore, 2024)	ECO	Three Dataset: Diabettic Retinophaty, Nephropathy, dan Neurophathy	The proposed model provided minimum error
(Nivetha et al., 2024)	BFHO	PIMA	BFHODL-NIDDC as proposed model got accuracy of 94.92%
(Ur Rehman & Khanum, 2014)	CS	PIMA	SOFRM got accuracy and classification rate 98.31%
(Alirezaei et al., 2019)	MOFA	PIMA	MOFA and MOICA achieved 100% classification accuracy

Tab. 3f. Search results of other metaheuristics algorithm-based usage and their performances, continuation

Authors	MA	Dataset	Performance result
(Selvakumar et al., 2019)	BHS	Custom 4	BHS-Decision Tree got Accuracy 92.87%
(Faraji-Biregani & Nematbakhsh Nasser, 2019)	SCA	Custom 5	The proposed method obtained minimum error less than 0.0017.
(Haghighi & Hoseini, 2020)	BFFA	PIMA	The proposed method demonstrated superior accuracy in diagnosing Diabetes compared to the PSO, FA, SHO and HHO algorithm
(Sreejith et al., 2020)	CE	PIMA	The classifier achieved 89.04% accuracy for the Diabetes dataset
(Khurma et al., 2020)	MFO	PIMA	RMFO Got accuracy to 80%
(Aslam et al., 2021)	FEA	130-US Hospital	The study achieved the highest accuracy of 99%
(Samreen, 2021)	CSO	ES	The algorithm got accuracy of 98.4%

Dataset used in papers:

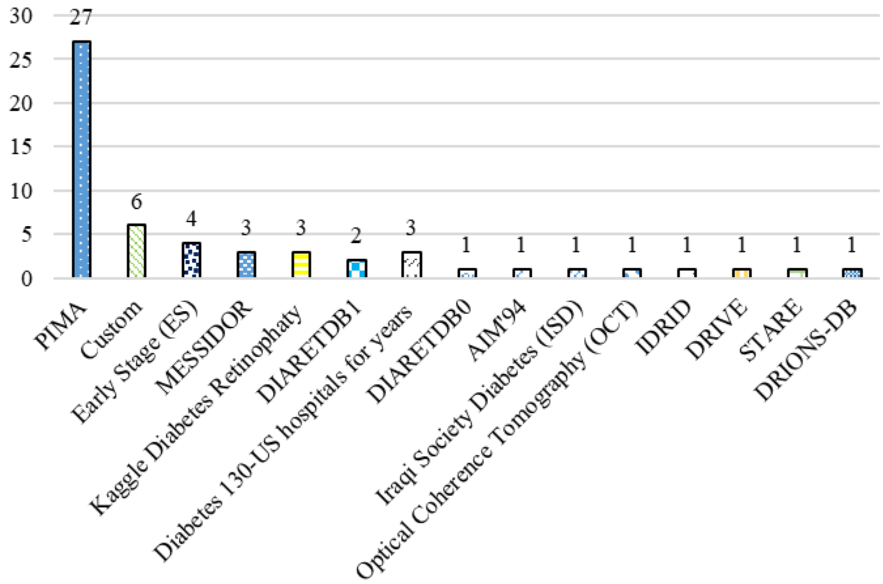

Fig. 3. Datasets used in selected papers

Publisher in papers:

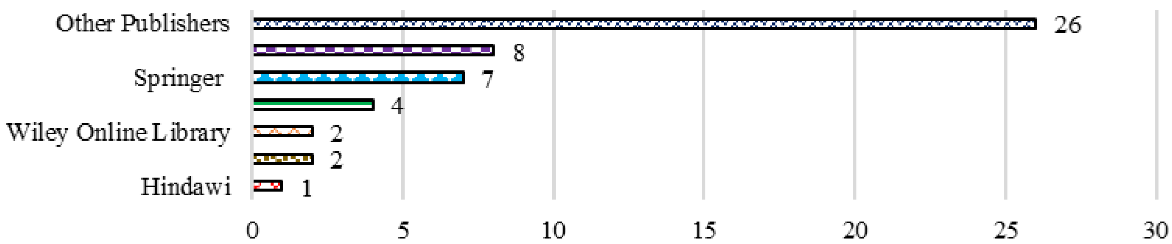

Fig. 4. Paper publishers

Challenges:

Tab. 4. Challenges of the metaheuristics algorithm in papers

The performance metric is still low.	Classification performance is still low; there is a potential for model overfitting, which is a challenging factor in classification development (Welikala et al., 2015; Shankar & Manikandan, 2019; Mallika & Selvamuthukumaran, 2021; Abdollahi & Nourimoghaddam, 2023; Hoda & Nadimi-Shahraki, 2016; Yasaswini & Baskaran, 2021; Majhi, 2019; Gadekallu & Khare, 2017; Salman et al., 2018).
High Computational	Computation time is long enough to make the model inefficient, and the model is heavy/complex.(Nagaraj et al., 2021; Samreen, 2021)

4. DISCUSSION

4.1. RQ1: What are the most commonly used metaheuristic algorithm?

This study reviews various studies on Diabetes prediction using various metaheuristic algorithms for feature selection. Figure 5 presents the algorithms used in the literature and the number of studies using each algorithm. The number of studies using each algorithm is also listed to show how commonly the algorithm is used in this context. The presentation of this data can provide important information for the reader regarding the trends in using certain algorithms in Diabetes prediction research using metaheuristic approaches.

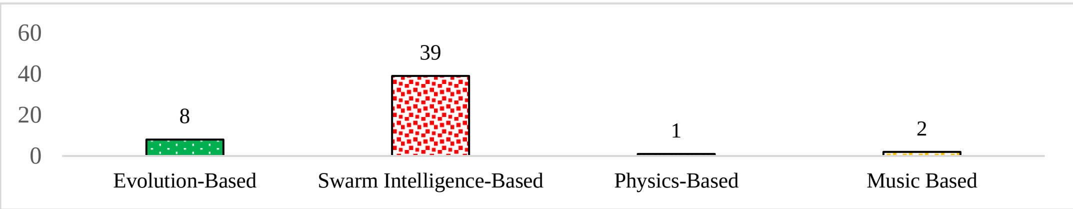

Fig. 5. Comparison of each metaheuristic algorithm categories usage in SLR

These algorithms perform feature selection for the Diabetes classification/detection process with the ML algorithm. This SLR reviews three categories of Metaheuristic algorithms: Evolution-based, Swarm Intelligence-based, Physics-based, and Music-based. The results in Tab. 3a-3f show that the Metaheuristic algorithm category most used in studies on Diabetes prediction is the Swarm Intelligence-based category, with a total of 39 papers. The popular algorithms used in this category are GWO and PSO, with four studies each. The Swarm Intelligence-based algorithms are the most popular method, especially in the feature selection task. The ability of the Swarm Intelligence to perform feature selection in exploring and exploiting the search space is easy to accomplish with various combinations of algorithms. This is one of the factors why many studies use Swarm intelligence to perform feature selection, especially on medical datasets. Furthermore, the Evolution-based category occupies the second position with eight papers. Metaheuristic algorithms in this category get the most papers on GA algorithms with eight, followed by MA with one paper. Then, another category is the Physics-based category which is as much as one paper by applying MVO. The last is the Music-based using Harmony Search (HS) with 2 papers

4.2. RQ2: What types of datasets are often used by researchers related to Diabetes prediction using Metaheuristic Algorithm?

This study used several datasets with different specifications to evaluate the Metaheuristic algorithm for the feature selection method and calculate how many papers used the datasets. Essential characteristics and description of the dataset are summarized in Fig. 3. The usage of the Tabular dataset is described in Tab. 5 Apart from that, this SLR has a custom dataset with different processes, such as collecting questionnaires and direct observation at the hospital.

Tab. 5. Description of tabular medical dataset

Dataset	Feature	Instances	Classes	No. Study	Sources
PIMA	8	768	2	31	(UC Irvine Machine Learning Repository, 2016)
ES	17	520	2	3	(UC Irvine Machine Learning Repository, 2020)
ISD	14	1000	3	1	(Rashid, 2020)
130-US	47	101766	2	2	(Clore et al., 2014)
Custom 1	10	1019	2	1	(García-Domínguez et al., 2023)
Custom 2	13	N/A	2	1	(Gadekallu & Khare, 2017)
Custom 3	18	950	3	1	(J. Li et al., 2022)
Custom 4	22	306	2	1	(Nagaraj et al., 2021)
Custom 5	23	732	2	1	(Selvakumar et al., 2019)
Custom 6	11	N/A	N/A	1	(Faraji-Biregani & Nematbakhsh Nasser, 2019)

The data obtained are ten datasets with different characteristics for each dataset in predicting Diabetes. Among the 41 research studies utilizing tabular datasets, the PIMA dataset was the most frequently employed, featured in 31 papers. Originating from the National Institute of Diabetes and Digestive and Kidney Diseases, this dataset holds prominence. Additionally, the ES dataset, referenced in 3 papers, originates from the Sylhet Diabetes Hospital in Bangladesh. The 130-US dataset is also used in as many as 2 papers. This dataset represents ten years (1999-2008) of clinical care at 130 US hospitals and integrated delivery networks. Another dataset is ISD with one paper; data were acquired from the laboratory of Medical City Hospital and The Specializes Centre for Endocrinology and Diabetes-Al-Kindy Teaching Hospital. In addition, this publication contains six custom datasets; Custom-1: patient data from Mexico's governmental hospital Centro Médico Siglo XXI (García-Domínguez et al., 2023), Custom-2: a real-time Diabetes database obtained from the Sree Diabetic Care Centre in Kurnool, Andhra Pradesh (Gadekallu & Khare, 2017) and score matching (PSM) based case-control study (J. Li et al., 2022), Custom-3: among the 950 participants enrolled from the second affiliated hospital of Wenzhou Medical University (WMU), and Custom-4: a dataset of Type 1 Diabetes mellitus data collected from various hospitals and diagnostic centers in Dhaka, Bangladesh by using questionnaires (Nagaraj et al., 2021), Custom-5: dataset collected from the hospital of Oman with the additional features like cholesterol, hip and waist circumferences, lastly, Custom-6: a dataset was extracted from the test results of diabetic patients in Isfahan city.

Tab. 6. Description of image dataset

Dataset	Total Images	No. Study	Sources
APTOS2019	3662	1	(Asia Pacific Tele-Opthamology Society, 2019)
DIARETDB0	130	1	(Kauppi et al., 2007)
DIARETDB1	89	2	(Kauppi et al., 2021)
OCT	75	1	(Balakrishnan et al., 2016)
KDR	88702	3	(Cukierski, 2014)
MESSIDOR	1200	3	(Decencière et al., 2014)
DRIVE	40	1	(Staal et al., 2004; Larxel, 2020)
STARE	81	1	(Hoover & Goldbaum, 2003)
DRIONS-DB	110	1	(Carmona et al., 2008)

Another dataset found in the papers is the image dataset related to diabetic retinopathy (DR), shown in Tab. 6 DR is a syndrome in which the retina is damaged as a result of complications of diabetic retinopathy, leading to irreversible visual impairment such as for some cases. The possibility of untreated patient blindness highlights this type of problem among patients. Ten image materials were found, each with a different number of images. The APTOS 2019 dataset is data from the 4th Asia Pacific Tele-Ophthalmology Society (APTOS) Symposium, with a total of 3662 images (Vijayalakshmi & Kumar, 2022). Two versions of the DIARETDB dataset were also found in the papers; DIARETDB0 with 130 images (Abdullah et al., 2018) and DIARETDB1 with 89 images (Jadhav et al., 2021). Moreover, the Optical Coherence Tomography (OCT) dataset with 75 images was used (Karthikeyan & Alli, 2018). The dataset with the highest number of studies is Kaggle Diabetic Retinopathy (KDR), with 88702 data used by three research papers Aslam et al., (2021) and Bilal et al., (2022). Similar to KDR, the MESSIDOR dataset was used in three papers with 1200 image data. Other observations used datasets from the Digital Retinal Images for Vessel Extraction (DRIVE) with 40 images, the STARE, and the DRIONS-DB dataset with 110 images were also studied.

4.3. RQ3: What is the best-performing Metaheuristic Algorithm?

Recent studies have assessed the effectiveness of several metaheuristics across diverse datasets which is summarized in Fig. 6. In the PIMA dataset, the Bumblebee and Flower Pollination Optimization (BFPO) algorithm achieved an accuracy of 98.7% that studied by Sutha et al. (2023). Notably, BFPO's success stems from its ability to identify highly relevant features efficiently, thereby enhancing classification performance without increased computational complexity. Conversely, in the ES dataset, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) stood out with an average accuracy of 98.86%, followed closely by the Crow Search (CS) at 98.42%, and both Grey Wolf Optimization (GWO) and Adaptive Parallel Grey Wolf Optimization (APGWO) reaching 96% and 97%, respectively. NSGA-II studied by Gupta et al. (2022) excels due to its robust handling of multiple objectives through the preservation of elite solutions across generations. Meanwhile, in the ISD dataset study, X. Li et al. (2023) developed Recursive Feature Elimination (RFE) and Genetic Algorithms (GA) demonstrated strong performance. RFE improved K-nearest neighbor's balanced accuracy significantly by focusing on top-five features like HbA1c, BMI, chol, triglycerides, and very-low-density lipoprotein cholesterol, whereas GA emphasized HbA1c as pivotal, yielding near-optimal results. Finally, in the 130-US dataset, The AFA demonstrated remarkable accuracy in predicting outcomes, achieving a success rate of 99.93%, as reported by Nagaraj et al. (2021) This exceptional performance was largely attributed to its ability to assess the contribution of features to classification accuracy while effectively minimizing redundancy among the selected attributes.

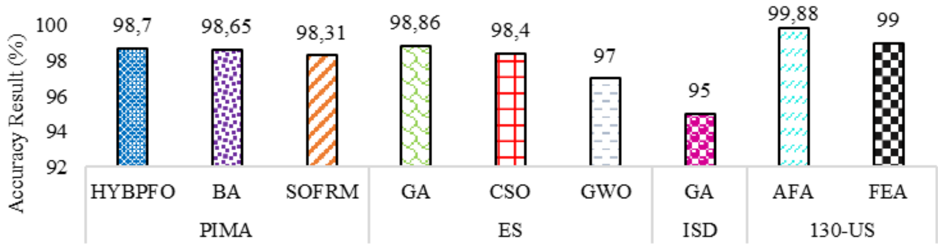

Fig. 6. The presentation of the best-performing algorithm of each tabular public dataset

Figure 7. shows that we can examine the algorithms' performance metrics across an image dataset. The primary distinction between tabular and image data lies in their fundamental structure and how they are presented. While tabular data is structured in rows and columns, image data comprises pixels that form the visual content. These differences influence the choice of the most suitable algorithms and the necessary pre-processing steps before inputting the data into a model.

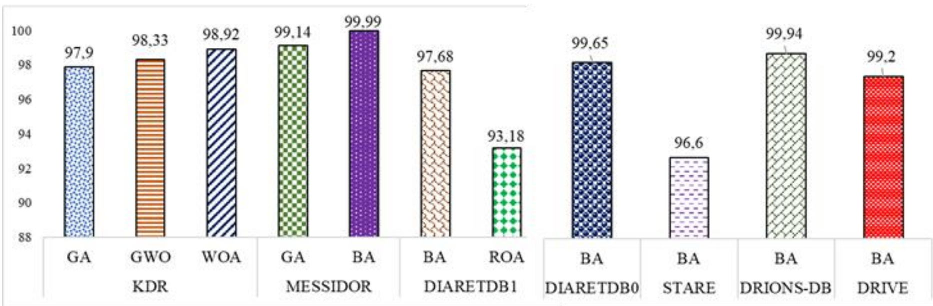

Fig. 7. The presentation of the best-performing algorithm of each image dataset

In the MESSIDOR dataset obtained a perfect accuracy of 99.99% using the BA (Abdullah et al., 2018). BA is used to find the optimal threshold value for the optic disc location. In order to improve the accuracy of the segmented optical disc and obtain the best result, in the last step, the elliptic fitting method was used to refine and smooth the boundary area of the segmented optical disc. Elliptical fitting is performed using the least-squares distance method. Experiment on the DIARETDB1 dataset which obtained an accuracy of 97.68% was explored (Abdullah et al., 2018). As shown in Figure 10, the DIARETDB0 dataset was also used, obtaining an accuracy of 99.65%, along with the DRIONS-DB dataset (99.42% accuracy), the DRIVE dataset (99.20% accuracy), and the STARE dataset (96.62% accuracy). Additionally, the APTOS2019 dataset using the GWO algorithm gets an accuracy of 94.11% (Vijayalakshmi & Kumar, 2022). This approach was chosen for its ability to explore and exploit the search space efficiently, ensuring convergence to the global optimum. The researchers worked to improve the performance of the GWO algorithm by addressing its shortcomings, such as convergence speed and accuracy, which led to the development of the Improved Grey Wolf Optimization (iGWO) algorithm.

Feature selection is a crucial preprocessing step in machine learning, particularly in medical diagnostics, where high-dimensional data can lead to increased computational complexity and reduced model interpretability. This systematic literature review (SLR) also examines the comparative effectiveness of various metaheuristic algorithm-based feature selection techniques in detecting diabetes, with a specific focus on computational cost or processing time that is presented in Tab. 7.

The analysis presented in Tab. 7 highlights the significant contributions of Genetic Algorithm (GA)-based methods, such as GA-KNN and GA-XGBOOST, in reducing computational cost while maintaining high accuracy. GA-KNN demonstrated minimal accuracy loss (2.869%) alongside reduced computational cost, while GA-XGBOOST showcased superior efficiency, achieving a significantly lower execution time of 06:17.415970 on the CDC diabetes dataset. Similarly, Recursive Feature Elimination (RFE) combined with KNN improved balanced accuracy by 20%, underscoring its effectiveness in refining feature selection. Furthermore, FFA emerged as the fastest approach among those evaluated, outperforming both PSO and HBA. The BMNABC algorithm, applied to a merged dataset from the US and Iranian Ministry of Health, efficiently reduced feature dimensionality while achieving an impressive processing time of 0.04825 seconds. Additionally, PSO-GA-SVM demonstrated competitive performance, attaining 93% accuracy with a processing time of 141.47 seconds. Notably, the hybrid HWOPSO-WOA method proved to be the top performer, achieving 97.3% accuracy while maintaining an optimal processing time of 98.45 seconds.

Overall, this study underscores the importance of selecting an appropriate metaheuristic-based feature selection method in diabetes diagnosis. Metaheuristic algorithms alone generally have lower computational cost compared to hybrid approaches because they involve fewer combined algorithmic steps. They are known for solving complex problems and achieving optimal solutions with less computational complexity (Blum et al., 2010). The key advantages of applying standalone metaheuristics are as follows: First, metaheuristics provide a general algorithmic framework that can be applied to a wide range of optimization problems with relatively few modifications. Second, they enable efficient exploration of the solution space; algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) effectively identify optimal feature subsets, improving prediction accuracy while reducing computational cost (S. Agrawal et al., 2024). Lastly, while hybrid approaches combine metaheuristics with other techniques to enhance performance, they often introduce increased complexity and higher computational demands.

The main drawbacks of using hybrid metaheuristics over standalone metaheuristics are related to computational cost, scalability, and difficulty in generalization. In terms of computational cost, hybrid metaheuristics are more computationally expensive; however, they often provide a better exploration-exploitation balance and deliver higher-quality solutions for many complex optimization problems.

Regarding scalability, hybrid techniques can struggle, particularly when managing dynamic and stochastic demands, and integrating real-time data. Lastly, hybrid algorithms may have limited generalization capabilities beyond specific, diverse real-world scenarios. While a hybrid approach might excel for certain problems, it could perform poorly for others, restricting its broader applicability (Blum et al., 2011).

Tab. 7. Comparison algorithm by computational cost

Study	Dataset	Method	Results
(X. Li et al., 2023)	PIMA	GA-KNN (Standalone)	Feature Selection with GA contribute to reduce computational cost with minimal 2.86% loss of accuracy
(X. Li et al., 2023)	ISD	RFE-KNN (Standalone)	Balanced Accuracy increased 20% when applying RFE as feature selection which obtained 96% of accuracy.
(Bekaddour et al., 2017)	PIMA	FFA (Standalone)	The FFA was the fastest, executing in less time than PSO and HBA.
(Aliyu et al., 2024)	Centers for Disease Control and Prevention (CDC) diabetes dataset	GA-XGBOOST (Standalone)	GA-tuned XGBOOST classifier on the PSO-balanced dataset exhibits significantly lower computational time recorded 06:17.415970
(Pradhan et al., 2024)	Merged130 US and PIMA, Iranian Ministry of Health dataset	BMNAC (Hybrid)	The BMNABC algorithm efficiently selects features, reducing dimensionality and improving classification performance. with a computation time of 0.04825 seconds
(Navazi et al., 2023)	ES	PSO GA-SVM (Hybrid)	GA SVM obtained run time of optimization part (seconds) 141.47s and achieve 93% of accuracy
(Raj et al., 2024)	IDRiD	HWOPSO-WOA (Hybrid)	The Proposed technique stands out as the best performer, with an accuracy of 97.3% and showcasing efficiency with a processing time of 98.45 seconds
(Bhimavarapu & Battineni, 2022)	DIARETDB0	PSO and Discrete PSO (Standalone)	The average runtime for PSO is approximately **18.11s**, while the average runtime for Discrete PSO is approximately **17.67s**

Future research should focus on exploring further optimization strategies to enhance the real-time applicability of these methods in clinical settings.

4.4. RQ4: Where have the paper articles related to diabetes prediction using metaheuristic algorithms been published?

Research publications related to applying metaheuristics and ML algorithms can be seen in Fig. 4. There are eight papers published by Elsevier and seven by Springer. Elsevier and Springer are the world's largest and most reputable academic publishers. Their journals have a high impact factor and are read by professional researchers worldwide. IEEE followed the next publications with four papers, MDPI with 2 papers. There were 26 papers published elsewhere.

4.5. RQ5: What challenges are experienced in each article when applying metaheuristic algorithms?

Table 4 presents some of the challenge's researchers encounter in developing metaheuristic algorithms for the early detection of diabetes. The primary challenge is that the performance of these models has yet to be fully optimized. Some papers have experienced this by experimenting with Metaheuristic algorithms and ML algorithms. For example, while using PIMA, Astuti et al. (2022) with BWOA and Naïve Bayes algorithms got 76% accuracy, Hoda and Nadimi-Shahraki (2016) by using modified BA method got 78.57% accuracy. With the same dataset, Yasaswini & Baskaran (2021) by using the FFA got 79% accuracy and Hartono (2022) by using MOBA achieved 77.5% accuracy. ML models can be very diverse based on the type of problem. No one model fits all problems (No Free Lunch). If the same dataset is used in experiments using different metaheuristic algorithms, it will produce different accuracy. Especially in the case of feature selection, the Metaheuristic Algorithm may not always fit the experimental dataset. Therefore, there are several techniques are needed to improve classification performance, such as developing right choices of classifier or hyperparameter-tuning ML parameters. The selection of a classifier is a crucial step in machine learning, as it directly influences the accuracy and efficiency of predictive models. Furthermore, Hyperparameter tuning plays a crucial role in enhancing the performance, accuracy, and efficiency of machine learning models. By optimizing key parameters such as learning rate, regularization strength, and model complexity, it helps strike a balance between underfitting and overfitting, ensuring better generalization to unseen data. Various techniques, including grid search, random search, and more advanced optimization algorithms, can be used to automate and refine this process (Ali et al., 2023). So, with this challenge, research related to metaheuristic algorithms in Diabetes cases is still open.

The next challenge is the high computational cost, which imposes certain limitations. Using multiple datasets with various attributes tends to increase computational complexity, which should be minimized (Nagaraj et al., 2021). Nagaraj et. al. mainly focused on the computational cost of the AFA feature selection method. They also discussed various feature selection techniques, such as Filter, Wrapper, and Hybrid methods. For example, the Wrapper method, which evaluates a subset of features based on a specific classification technique, incurs significant computational cost due to its dependence on the classification method results. In contrast, Filter methods, which select features based on data features without using classification methods, face limitations in terms of adaptability. Then, Hybrid methods aim to achieve a balance between efficiency and effectiveness by combining the characteristics of filter and wrapper methods. Likewise, the challenge when using CS for feature selection, the execution time may be higher due to the increased number of iterations in the CS algorithm, which is aimed at achieving improved classification accuracy (Samreen, 2021). Utilizing the Crow Search (CS) algorithm for feature selection may result in longer execution times, as the CS approach requires a greater number of iterations to achieve improved classification accuracy.

The algorithm entails the initial placement of a group of crows within the search area, their awareness of being pursued by other crows, updates to their flight path based on the likelihood of awareness, a predetermined flight distance, storage of the best position discovered thus far, and repetition of these steps until a stopping condition is satisfied. The increased number of iterations in the CS algorithm guarantees a comprehensive exploration of the search space to identify the ideal combination of characteristics that yields the highest classification performance. The comprehensive examination of the search space can lead to a prolonged execution time, which can be problematic in situations where speed is of utmost importance. Nevertheless, the algorithm's capacity to optimize the parameters of the feature selection process renders it a potent tool for enhancing classification accuracy in diverse applications.

To mitigate these challenges, strategies such as parameter tuning, parallel computing, and hybrid optimization approaches can be employed. Parameter tuning can help optimize algorithm performance by selecting appropriate values for hyperparameters, reducing unnecessary computations. Next, Parallel computing techniques can distribute the computational workload across multiple processing units, significantly decreasing execution time. Additionally, hybrid optimization approaches, which integrate metaheuristic methods with deterministic algorithms, can improve convergence speed while maintaining classification accuracy. Incorporating these strategies can enhance the practicality and scalability of feature selection methods in real-world applications (Chowdhury et al., 2022).

Therefore, research related to metaheuristic algorithms is still open to find algorithms that have low computation and high accuracy.

5. CONCLUSION AND SUGGESTIONS

Diabetes is a risky disease if not treated quickly. AI technology based on ML is one of the solutions that can be used for Diabetes early prediction. However, ML has drawbacks, such as high feature dimensions, noise features, and high computational cost. Feature selection methods can solve these problems because they can be used to reduce feature dimensions, remove noise features, reduce computation, and improve the performance of classification algorithms. This SLR discusses early detection of Diabetes using feature selection based on metaheuristic algorithms. Based on the analysis results, the Swarm Intelligence-based metaheuristic algorithms are the most widely used by researchers due to their performance and ease of implementation. Then, the PIMA dataset is the most frequently used tabular dataset, being cited in up to 31 research papers. The metaheuristic algorithms with the best performance are HYBPFO for the case of tabular datasets and BA for the case of image datasets. The challenges in applying metaheuristic algorithms in the case of Diabetes prediction, such as obtaining low-performance, unsuitable parameters, high computation, and local optima. This aligns with the No Free-Lunch theorem in metaheuristic algorithms, which means no single algorithm is best for all problems. Each case is unique, so there is open opportunity for further research on early Diabetes prediction using these algorithms.

The analysis has identified key areas for future research, including the exploration of underutilized metaheuristic algorithms, the development of hybrid approaches that combine multiple techniques to improve prediction accuracy, and the implementation of case studies in clinical settings to evaluate practical applications. Additionally, the importance of interdisciplinary collaboration between data scientists and healthcare professionals is emphasized to develop comprehensive models that consider various factors influencing diabetes.

Additionally, for metaheuristic algorithm-based diabetes prediction to be effectively applied in clinical practice, it must adhere to regulatory compliance. AI-based medical tools require extensive validation and approval from authorities such as the Food and Drug Administration (FDA) and Conformité Européene (CE) mark. This process can be streamlined by integrating automated validation pipelines that align with medical regulatory standards. Furthermore, ensuring data privacy and security under regulations like HIPAA and GDPR necessitates the implementation of local deployment options.

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