Exploring The Efficiency of Metaheuristics in Optimal Hyperparameter Tuning for Ensemble Models on Varied Data Modalities

Vivek BC[1]

[1]Alliance College of Engineering and Design, Alliance University, Bangalore, India

Abstract

Effective disease detection systems play an important role in healthcare by supporting diagnosis and treatment. This study provides a comparison of hyperparameter tuning methods for disease detection systems using four health datasets; kidney disease, diabetes detection, heart disease and breast cancer detection. The main objective of this research is to prepare datasets by normalizing the input and testing machine learning models such as Naive Bayes Support Vector Machine (SVM), Logistic Regression and k Nearest Neighbor (kNN). to identify effective models for each data set. After implementing the models, we apply three hyperparameter tuning techniques: Grid search, random search, and particle ensemble optimization (PSO). These methods are used to tune the model parameters. Improve overall performance metrics. The evaluation focuses on accuracy measurements to compare model performance before and after hyperparameter tuning. The results of this study illustrate how different tuning techniques can improve the performance of disease detection systems across a range of healthcare datasets. By conducting testing and analysis, we determine the appropriate tuning method for each data set, yielding valuable insights, to develop an accurate and effective disease detection system. These discoveries serve to advance the field of healthcare analytics and machine learning to deliver outcomes for patients and healthcare services.

1. Introduction

In today's technology-driven society, widespread use of Internet programs has become fundamental in daily life, leading to an increasing number of Internet users [1]. Unfortunately, this acceleration in activity has also attracted cybercriminals to exploit vulnerabilities through phishing attacks, posing huge risks to online customers. Phishing attacks, characterized by phishing methods such as phishing emails and social media posts, aim to trick people into revealing sensitive information or installing malware. The increasing frequency of phishing attacks highlights the urgent need for robust cybersecurity measures [2].

Handling demanding cybersecurity scenarios including phishing attacks requires progressive tactics, such as AI-based frameworks to independently detect phishing URLs. Traditional techniques such as URL blacklisting or whitelisting have difficulty keeping up with developments in phishing techniques, which require very sophisticated detection mechanisms. ML and DL models provide promising avenues to identify phishing URLs by reading various features extracted from datasets [3]. Furthermore, in healthcare, early detection and prognosis of diseases such as coronary heart disease are essential to improve patient outcomes. ML algorithms have shown great promise in assisting medical professionals in their responsibilities of prognosis and prediction of disorders. For example, ML models have been hired to study coronary heart disease

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[1]Corresponding author. Email: bvivekBTECH20@ced.alliance.edu.in

datasets using techniques including logistic regression, support vector machines (SVM), decision trees, and pooling techniques [5].

Additionally, during global health crises including the COVID-19 pandemic, ML algorithms have played a key role in developing diagnostic and prognostic models largely based on medical data, clinical and laboratory evaluation. These models help predict outcomes associated with the need for intensive care and mortality risk, thereby helping healthcare providers make informed choices [2].

This research paper seeks to contribute to improving disorder detection systems and cybersecurity measures by exploring robust hyperparameter tuning techniques for ML models on a variety of other datasets [1], [2], [3]. In particular, we identify datasets related to kidney disease, diabetes detection, coronary heart disease, breast cancer detection. Leverage device mastering models including SVM, Naive Bayes, Logistic Regression, OK Nearest Friends (kNN), and use hyperparameter tuning strategies such as grid search, random search, and dark particle swarm optimization (PSO), we intend to explore the best tuning strategies to increase release performance and measurement accuracy. Our research strives to provide valuable insights into optimizing disease detection systems and enhancing cybersecurity protocols, deriving long-term benefits from the epidemic health care services and Internet protection.

The paper is based as follows: section 1 introduces the problem, highlighting its importance and the strategies used to address it. phase 2 evaluations modern-day research studies, special descriptions of the experimental dataset and detection approach are provided in section 3, segment 4 offers the experimental outcomes and compares them with findings from different datasets. subsequently, phase 5 offers the paper's give up.

2. Related Works

In the field of phishing URL detection, major studies have deployed datasets as well as the UCI and Mendeley phishing datasets. In study [1], they compared systems learning (ML) techniques using a variety of datasets, highlighting random forests and ensemble neural networks achieving accuracy 90 seven degrees. In study [2], they thoroughly implemented the UCI fraud dataset, showing the importance of feature selection strategies to obtain highly accurate quotes. In study [3], they proposed an anti-phishing device that combines URL and website features with an ML algorithm, where a random forest region showed impressively consistent overall performance. In study [15], they highlight the importance of features in phishing detection, with devices D and E showing high accuracy through the use of a set of random forest principles. In [6], we compare ML models on ad-hoc phishing datasets, favoring Random Forests for its accuracy. In study [7] and [8], we also analyzed the effectiveness of ensemble classifiers, where a random forest region performed

consistently well. Study [9] provided a green stacked set technique for online detection of phishing websites, achieving high accuracy on excellent datasets.

When it comes to health monitoring, especially predicting coronary heart disease and assessing bone fracture risk, machine learning strategies have shown promise in study [4], determined the prevalence of ML algorithms in predicting coronary heart disease outcomes and fracture risk after OVCF. ML algorithms play an important role in early detection and prevention techniques for coronary heart disease, improving patient outcomes in study [4]. During the COVID-19 pandemic, ML strategies have played an important role in predicting the consequences of pollution. Advanced prediction models in study [5] for COVID-19 diagnosis and mortality risk use deep reading algorithms and blood analysis. ML algorithms were also instrumental in developing COVID-19 diagnostic and prognostic models based entirely on CT images, blood tests, and scientific records of study [5]. Hyperparameter optimization (HPO) is crucial to enhance the conventional overall performance of ML models in study [5]. Recommendations for choosing an appropriate HPO algorithm, determining the tuning search domain, and implementing robust resampling techniques are important for the performance of the simplest version of study [5].

The reviewed articles ([1]-[15]) provide a comprehensive exploration of future engine learning (ML) algorithms and hyperparameter optimization in several fields of study [1] examines phishing URL detection, focusing on the impact of high-quality ML models. Furthermore, study [2] focuses on heart disease prediction if needed, highlighting the impact of the largest number of relevant hyperparameters on the performance of the instance. In healthcare, study [3] compared ML algorithms to predict fractures after spinal compression techniques, while study [5] focused on COVID-19 prognosis, showing the extent of ML software in infection management. It is worth noting that study [4] tests the accuracy of ML rule sets in language assessment, thereby contributing to studies on linguistic vowel type achievement. Furthermore, [6] advanced computerized detection of EMG activation timing through the use of ML, demonstrating applications in biomedical sign processing study [7] and [10] focus on mental age prediction and diabetes prediction, respectively, thereby strengthening the characteristics of ML in healthcare analytics and predictive modelling.

Beyond healthcare, study [8] discusses awkward hyperparameter optimization scenarios that are important for optimizing the typical overall performance of ML models at a given time for many applications use. Study [9] and [11] are well known for optimizing ML complexity and coronary artery disease sophistication, respectively, providing insight into specific conditions and algorithmic trauma solutions. Study [12] evaluate meta-analysis strategies, providing a comprehensive view of ML instance synthesis techniques. Furthermore, study [13] provides a comparative review of ML algorithms for pollution prediction, highlighting the

importance of desired recommendation set and parameter tuning to achieve accurate prediction. Finally, study [15] studies optimization characteristics, which reflect the continuous development and diversification of ML methods at a given time in the domain. Collectively, these studies highlight the dynamic landscape of ML research, emphasizing a set of guidelines on desirability, hyperparameter optimization, and their overall impact on the advancement of predictive analytics and systems aimed at creating desire in many areas.

3. Methodology and Implementation

This project is majorly developed with 4 stages- Data Collection, Data Pre-processing, Model Building, Performance Evaluation.

1) Data Collection: The research began with an extensive effort to accumulate relevant datasets focused on kidney disease, diabetes detection, heart disease, and breast cancer detection. These datasets are meticulously sourced from renowned scientific repositories, especially the UCI repository, which hosts a wide variety of datasets related to healthcare analytics. Each dataset in this study has a number of attributes and entries, ensuring a rich and comprehensive illustration of medical records across disease domains with high quality. This diversity is necessary to develop robust device research designs capable of accurately detecting and diagnosing disease in distinct clinical settings. Using a combination of datasets from formal assets with multiple attributes and inputs, this evaluation aims to improve the reliability and generality of state-of-the-art disease detection models. The datasets facts are as follows:

Chronical Kidney Disease Dataset: This is a dataset comprising of 14 different attributes and Binary class outcomes with 1 indicating that the person has a kidney disease, 0 indicating a healthy person. There's around 400 entries where 250 represents class '1', 150 represents class '0'.

Diabetes Dataset: This is a dataset comprising of 9 different attributes and Binary class outcomes with 1 indicating that the person is diabetic, 0 indicating a healthy person. There's around 768 entries where 268 represents class '1', 500 represents class '0'.

Heart Disease Dataset: This is a dataset comprising of 14 different attributes and Binary class outcomes with 1 indicating that the person is suffering from heart disease, 0 indicating a healthy person. There's around 1025 entries where 526 represents class '1', 499 represents class '0'.

Breast Cancer Dataset: This is a dataset comprising of 20 different attributes and Binary class outcomes with 1 indicating that the person is suffering from Malignant Breast Cancer, 0 indicating a Benign Breast Cancer. There's around 569 entries where 357 represents class '0', 212 represents class '1'.

2) Data Pre-Processing: Following collection, raw data sets undergo meticulous preprocessing

steps to improve ground-truth information and ensure consistency across all data sets. To address the imbalance in the distribution of sophistication across the datasets, we used random sampling to balance the input of each lesson, thereby providing fairness and reducing bias at any given point in the model education process. Furthermore, categorical variables had to be encoded as numerical representations and numerical capacities were normalized using the MinMaxScaler method. These preprocessing steps are essential to remove inconsistencies, handle missing values, and prepare the dataset for the next review and version development. By applying powerful preprocessing techniques as well as random oversampling and MinMaxScaler, we aim to generate standardized datasets that are beneficial for developing accurate detection instances sick.

3) Model Building: The selected machine learning algorithms – Support Vector Machines (SVM), Naive Bayes, Logistic Regression and k-Nearest Associates (kNN) – were chosen primarily based on their relevance and effectiveness in detecting disease in many different medical fields. These algorithms are popular because of their particular strengths in handling specific types of events and model complexity. To ensure effective training and evaluation of releases, the preprocessed datasets were 80: 20 divided into education and testing units. This partitioning strategy facilitates objective evaluation of instances while allowing for significant recording of algorithm training. Each algorithm gains individual expert knowledge of the school data, allowing them to look for problematic patterns and relationships in the data set, which is essential for accurate prediction and classification, validation at subsequent levels of testing and validation.

Pay special attention to the characteristics and suitability of each set of rules for specific data sets. SVM, recognized for its talent in handling multidimensional information with complex selection constraints, has been leveraged for responsibilities that require clear separation between formations. Naive Bayes classifiers, which are effective in handling large data sets and classify records through probabilistic modeling, were used because of their simplicity and computational efficiency. Logistic regression, which provides interpretability and insight into feature significance, has proven valuable for clinical record interpretation tasks. Furthermore, kNN, with its fully non-parametric and instance-based approach, successfully captures the local patterns required for the task of detecting epidemics characterized by comparable severity levels. These different options have facilitated a comprehensive evaluation, taking into account the strengths and barriers of each disease detection algorithm across different datasets and clinical domains. Ultimately, the model with the highest accuracy for every dataset could be recognized, and hyperparameter tuning techniques such as grid search, random search, and particle swarm optimization can be applied.

This step ambitions to optimize every model's hyperparameters to in addition enhance performance metrics like accuracy, sensitivity, and specificity. by way of evaluating the effectiveness of those tuning strategies across distinctive datasets, we intend to pick out the excellent tuning method for each respective dataset, contributing valuable insights to disease detection model refinement and optimization strategies in healthcare analytics research.

4) Performance Evaluation: The performance evaluation of each version is done by way of taking the metrics like Accuracy, Precision, F1-rating, for every version is a

respective dataset. For the Kidney sickness Detection Dataset, the version with maximum accuracy is KNN. For Diabetes Detection Dataset, the version with maximum accuracy is likewise KNN. The model with maximum accuracy for coronary heart ailment Detection Dataset is SVM. The model with maximum accuracy for Breast cancer Detection Dataset is Logistic Regression.

Table 1. Depicting the performance metrics of each datasets with respect to their algorithms

Dataset Used	ML Algorithms Used	Performance Metrics			
		Accuracy	Precision	Recall	F1-Score
Kidney Disease Dataset	KNN	96	95.989	95.989	95.989
	SVM	96	96.052	96.25	95.997
	Logistic Regression	96	96.052	96.25	95.997
	Naïve Bayes	94.666	94.871	95	94.666
Diabetes Dataset	KNN	75	75.05	74.839	74.876
	SVM	73.666	73.631	73.584	73.6
	Logistic Regression	74.666	74.644	74.679	74.648
	Naïve Bayes	73	73.348	73.21	72.985
Heart Disease Dataset	KNN	87.341	91.082	87.73	84.615
	SVM	90.189	92.073	90.69	89.349
	Logistic Regression	84.493	86.144	85.373	84.615
	Naïve Bayes	81.962	82.183	83.381	84.615
Breast Cancer Dataset	KNN	96.279	96.278	96.278	96.278
	SVM	96.279	96.291	96.283	96.278
	Logistic Regression	97.674	97.68	97.672	97.674
	Naïve Bayes	92.558	92.569	92.562	92.557

4. Results and Outcomes

Evaluation of the device's learning algorithms on multiple healthcare datasets has yielded insights into their baseline performance on high-quality disorder detection tasks. Before hyperparameter tuning, each dataset had different levels of precision set using excellent algorithms. The kidney disease dataset had very good accuracy with sufficiently good nearest neighbors (kNN), demonstrating the effectiveness of the algorithm in capturing closely spaced patterns in the dataset. In comparison, the heart disease dataset achieved the best accuracy through the use of support vector machines (SVM), highlighting SVM's knack for handling multidimensional data with limited selection, complex selection, a common feature in information about coronary heart disease.

Additionally, the diabetes detection dataset validated its accuracy in a fashion with kNN, leveraging its skills in handling class obligations related to huge datasets and great limitations in beauty. The maximal breast cancer detection dataset, characterized by a specific feature set and class distribution, achieves very high accuracy with logistic regression, highlighting its interpretability and completeness, set of rules for such clinical statistical interpretations.

Those consequences underscore the significance of algorithm choice based on dataset traits and ailment detection requirements. The various accuracies executed with the resource of 1-of-a-kind algorithms in the course of datasets characterize the nuanced nature of illness facts and the want for tailored system analyzing techniques. transferring ahead, the focus will shift to hyperparameter tuning strategies

together with grid seek, random are looking for, and particle swarm optimization. via excellent-tuning the fashions' hyperparameters, we goal to decorate accuracy, sensitivity, and specificity, similarly refining the disorder detection fashions' performance. The comparative evaluation of hyperparameter tuning techniques across datasets will offer valuable insights into optimizing tool getting to know fashions for unique healthcare analytics obligations, ultimately contributing to greater accurate and dependable sickness detection systems in scientific workout.

After identifying the models with the nice accuracy for every dataset—okay-Nearest buddies (kNN) for kidney disorder, assist Vector Machines (SVM) for coronary heart illness, kNN for diabetes detection, and Logistic Regression for breast maximum cancers detection—we executed hyperparameter tuning techniques the use of grid are looking for, random seek, and particle swarm optimization (PSO). Grid are searching for and random seek are nicely-installed algorithms for hyperparameter tuning, on the identical time as PSO represents a more contemporary technique acknowledged for its overall performance in exploring complicated search regions. The accuracies of each dataset extensively elevated after hyperparameter tuning, indicating the effectiveness of those optimization techniques in enhancing model typical overall performance. Grid searching for systematically explored quite a number hyperparameter values described in a grid-like fashion, optimizing model parameters to reap higher accuracies. Random seek, but, sampled hyperparameter values randomly from predefined degrees, providing a extra stochastic exploration of the quest area. PSO, inspired by social behavior such as hen flocking or fish education, correctly navigated the hyperparameter area to locate top-first-class configurations for stronger model accuracy. The superior accuracies all through datasets underscore the importance of satisfactory-tuning version parameters for better predictive overall performance.

The grid searching for exhaustive seek approach, random are looking for stochastic nature, and PSO's swarm-based totally optimization all contributed to refining the models' choice barriers and feature representations, important to greater accurate sickness detection consequences. those findings not most effective validate the need of hyperparameter tuning in machine reading version improvement but additionally highlight the advantages of using diverse optimization algorithms to unique dataset traits. The comparative evaluation of grid search, random are searching for, and PSO in this context gives treasured insights into their efficacy in improving ailment detection fashions, paving the way for more reliable and particular healthcare analytics and choice help systems. The changes in accuracies of each dataset after imposing hyperparameter tuning is demonstrated beneath:

After applying hyperparameter tuning techniques including grid seek, random search, and particle swarm optimization (PSO) to the selected models with the highest accuracy for every dataset, we observed full-size upgrades in version performance across the board. to visualize these enhancements, we plotted graphs depicting the accuracies of each dataset earlier than and after tuning. The graphical representation clearly suggests the impact of hyperparameter tuning on enhancing the accuracies of ailment detection fashions. The plotted graphs function compelling visible evidence of the effectiveness of best-tuning model parameters in gadget mastering responsibilities, specially in healthcare analytics wherein particular disease detection is paramount. The comparative analysis not only validates the importance of hyperparameter optimization however additionally presents a clear roadmap for selecting the maximum appropriate tuning strategies primarily based on dataset characteristics, similarly contributing to the development of accurate and dependable sickness detection systems.
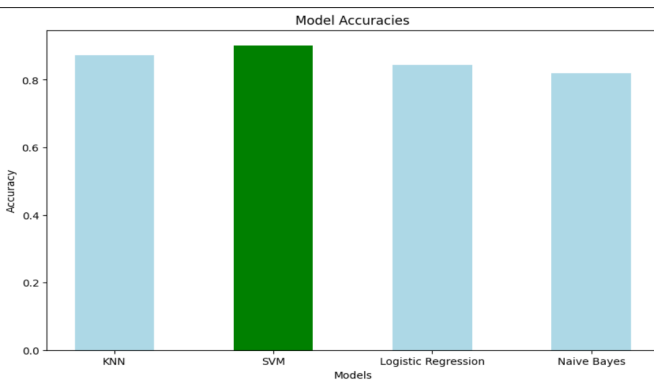

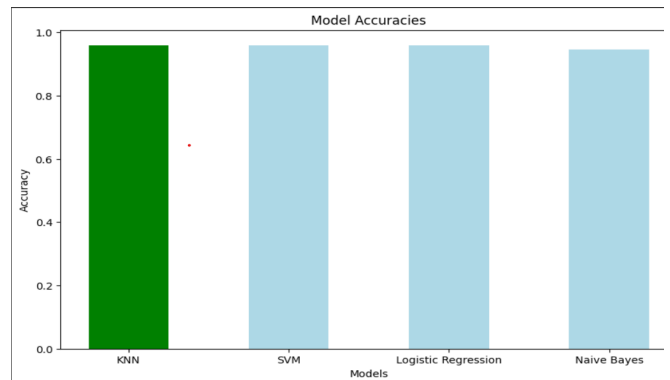**Figure 1.** Graph depicting model with highest accuracy for Heart-Disease Dataset

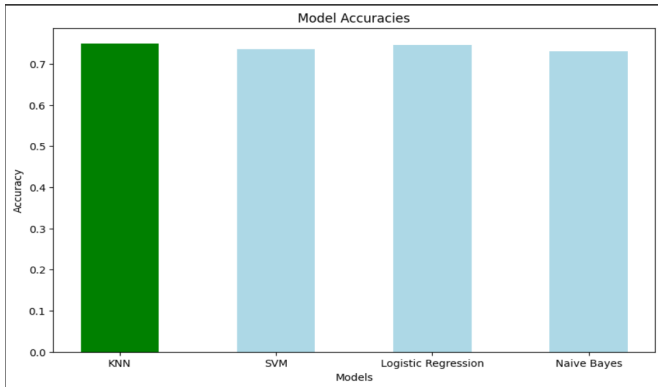**Figure 2.** Graph depicting model with highest accuracy for Kidney-Disease Dataset

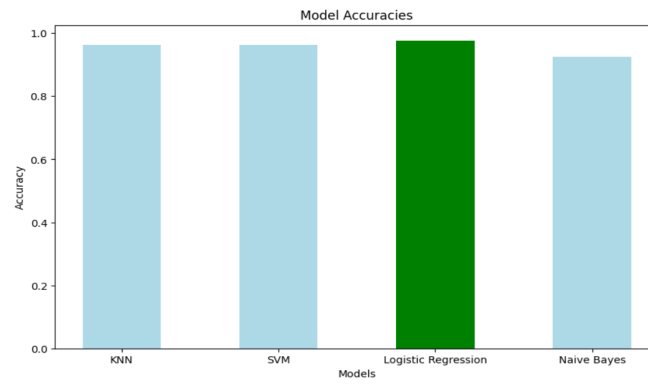**Figure 3.** Graph depicting model with highest accuracy for Diabetes-Disease Dataset

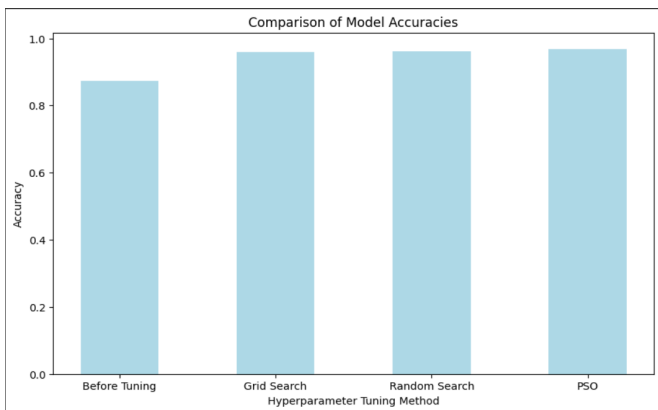**Figure 4.** Graph depicting model with highest accuracy for Breast Cancer-Disease Dataset

Figure 5. Graph depicting the comparison of accuracies of SVM model from Heart Disease Dataset before and after hyperparameter tuning techniques are implemented.
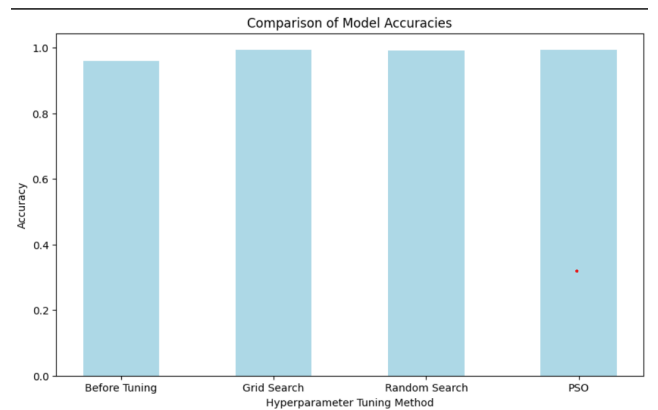

Figure 6. Graph depicting the comparison of accuracies of KNN model from Kidney Disease Dataset before and after hyperparameter tuning techniques are implemented.
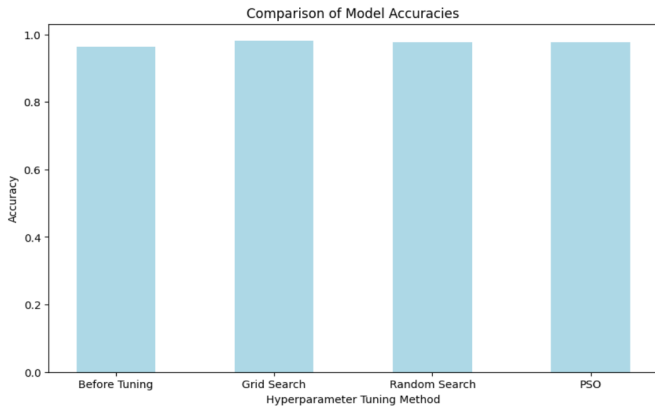
Figure 7. Graph depicting the comparison of accuracies of LR model from Breast Cancer Dataset before and after hyperparameter tuning techniques are implemented.
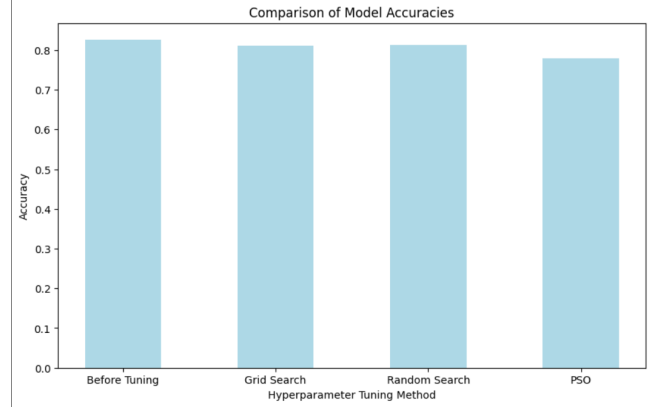
Figure 8. Graph depicting the comparison of accuracies of KNN model from Diabetes Dataset before and after hyperparameter tuning techniques are implemented.

Table 2. Depicting the accuracies of each datasets after hyper-parameter tuning

Dataset Used	Model with Highest Accuracy before Tuning	Hyperparameter Technique with improved accuracy
Kidney Disease	KNN - 96.000	Grid Search - 99.428
Heart Disease	SVM - 90.189	PSO - 96.872
Breast Cancer	Logistic Regression - 97.674	Grid Search - 98.195
Diabetes	KNN - 75.000	Random Search - 82.666

Table 3. Indicating the change in accuracies after comparing the hyperparameter techniques for models which obtained highest accuracy before implementing the hyperparameter tuning

Dataset Used	Model With Highest Accuracy	Hyper-Parameter Tuning Algorithms Used	Respective Accuracies for each tuning techniques
Kidney Disease	K-Nearest Neighbors	Grid Search	99.428
		Random Search	99.142
		Particle Swarm Optimisation	97.3333
Heart Disease	Support Vector Machine	Grid Search	95.918
		Random Search	96.195
		Particle Swarm Optimisation	96.872
Diabetes Detection	K-Nearest Neighbors	Grid Search	82.333
		Random Search	82.666
		Particle Swarm Optimisation	79.666
Breast Cancer	Logistic Regression	Grid Search	98.195
		Random Search	97.593
		Particle Swarm Optimisation	97.795

5. Conclusion and Discussions

The comprehensive review conducted in this study focuses on comparing machine learning algorithms for disease detection across multiple medical datasets, including kidney disorders, heart disorders, diabetes detection, and detect breast cancer. Our technique includes rigorous statistical preprocessing, instance training, and initial evaluation without hyperparameter tuning. In this first part, we identified the models with the best accuracy for each dataset: nearest knowledge (KNN) for kidney disease, support vector machine (SVM) for heart disease , New KNN for diabetes detection and logistic regression for breast cancer detection. Sooner or later, we applied hyperparameter tuning techniques including grid search, stochastic search, and particle ensemble optimization (PSO) to further optimize the selected models. The results show a significant increase in accuracy in all datasets after hyperparameter tuning. This improvement is especially significant when comparing accuracy before and after adjustment, as shown in the graphical representation. The graphs simply illustrate the effectiveness of hyperparameter optimization in improving build performance. The results of these studies highlight the essential role of hyperparameter tuning in fine-tuning device research models for disease detection.

The results of these studies highlight the essential role of hyperparameter tuning in fine-tuning device research models for disease detection. The choice of tuning method can significantly influence the accuracy and robustness of the release, with grid search and random search proving to be widely relevant and reliable techniques. Widely, while PSO has demonstrated its capabilities as a unique and effective optimization method. These results provide valuable insights to healthcare analytics researchers and practitioners, guiding them in selecting appropriate tuning techniques based purely on data set trends and model request.

In turn, this research contributes to advancing the field of machine control in healthcare by demonstrating the importance of hyperparameter optimization in developing accurate disease detection frameworks and reliable. Recommendations for future studies could also include exploring deeper hyperparameter tuning strategies, integrating mastering strategies, and evaluating the interpretability of releases under Generic performance metrics to further improve analytical and prognostic accuracy. By regularly refining systems research models through system tuning and evaluation, we can pave the way for more effective health analytics and enhanced patient outcomes.

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