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A Novel Concept of IOT Healthcare Monitoring Framework with Hybrid Optimization Techniques for Early Diagnosis of Cancer

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Abstract
Lung cancer is one of the deadliest diseases worldwide. Early detection is crucial for improving survival rates. Lung nodules are an important sign for early diagnosis. They help reduce the workload for radiologists and improve diagnostic accuracy. Artificial intelligence-based neural networks have shown promise in automating the detection of lung nodules by utilizing patient data collected from Internet-of-Things (IoT)-enabled healthcare systems. However, traditional models often depend on manually created features, which limits their diagnostic performance. In this study, we propose a new IoT-enabled healthcare monitoring framework that includes a Multi-Strategy Improved Grey Wolf Optimization (MSI-GWO) algorithm and a Capsule Network ELM: Extreme Learning Machine (CAPSNET-ELM) hybrid model for early lung cancer detection. To address the challenge of high-dimensional medical data, we employ an Artificial Bee Colony-Harris Hawks Optimization (ABC-HHO) algorithm for optimal feature selection. This improves the model's sensitivity and precision. We implement the proposed system using NS-2 for network simulation and TensorFlow-based Python libraries for training and deploying the model. The optimized CAPSNET-ELM hybrid classifier is trained on features extracted from the IoT platform and is evaluated against leading lung cancer detection models. We securely store diagnostic results in the cloud for clinical review, showing better performance in terms of accuracy, sensitivity, specificity, and precision.

Keywords: Internet-of-Things; Healthcare Monitoring; Lung Cancer; Artificial Bee Colony-Harris Hawks Optimization; Multi-Strategy Improved Grey Wolf Optimization; CAPSNET-ELM Hybrid; NS-2; TensorFlow

1. INTRODUCTION

Lung cancer is one of the most terrible diseases in developing countries, and its mortality rate is 19.4%. Early detection of lung tumours is done using several imaging techniques such as CT, sputum cytology, chest X-ray, and MRI. Neural networks are crucial for recognizing cancer cells among normal tissues, which provides a helpful tool for creating an AI-based cancer detection system. A technique based on Convolutional Neural Networks (CNN) to classify lung tumours as malignant or benign.[1]
Globally, lung cancer is the leading cause of cancer-related deaths. It is a serious public health issue. Lung cancer accounted for 1.8 million deaths (18%) in 2020, according to the International Agency for Research on Cancer's (IARC) GLOBOCAN 2020 estimates. During their lifetime, 1 in 16 men and 1 in 17 women will be diagnosed with lung cancer, according to the American Cancer Society in 2023. Generally, cancer

cells often move to the centre of the chest due to normal lymph flow. When cancer cells spread to other tissues, it is called metastasis. Since cancer tends to spread and become incurable with extensive spread, early detection is crucial. Lung cancer typically shows symptoms only in its later stages when survival becomes nearly impossible and diagnosis is difficult. Certain features must be identified and measured to find malignant nodules. The likelihood of cancer can be determined by combining these identified features. Even for an experienced doctor, this task is very difficult because it is challenging to correlate the presence of a nodule with a positive cancer diagnosis. To help with this, many studies suggest using Machine Learning (ML) and Deep Learning (DL) techniques for the early detection of lung cancer. Techniques include Support Vector Machine (SVM), Logistic Regression (LR), Convolutional Neural Network (CNN), K-Nearest Neighbour (KNN), Artificial Neural Network (ANN), Random Forest (RF), and many other algorithms. With the fast advancement of ML, it is important to determine which method offers the best performance for detecting lung cancer.[2]

Detecting lung tumours early involves various imaging techniques like Computed Tomography (CT), Sputum Cytology, Chest X-ray, and Magnetic Resonance Imaging (MRI). Detection means classifying tumors into two types: (i) non-cancerous tumours (benign) and (ii) cancerous tumours (malignant). The chance of survival at an advanced stage is lower compared to the treatment and lifestyle choices that support survival when diagnosed early. Manual analysis and diagnosis systems can see significant improvements with image processing techniques. Many studies have explored image processing methods for detecting early-stage cancer. However, the success rate for early detection has not improved much. With the rise of machine learning techniques, many researchers are working on early cancer diagnosis. Neural networks are crucial for identifying cancer cells among normal tissues, making them a valuable tool for developing AI-assisted cancer detection. Effective cancer treatment depends on accurately separating tumour cells from normal cells. The classification of tumour cells and the training of neural networks are essential for machine learning-based cancer diagnosis.[3]

Our contribution is threefold, as detailed below. 1. We developed an IoT platform, inferred the mechanism for acquiring lung disease data, and investigated the process for extracting the most significant attributes employing the Artificial Bee Colony–Harris Hawks Optimization (ABC-HHO) algorithm, which enables high accuracy in the diagnosis of lung cancer. 2. We investigate the mechanism of the Grey-Wolf Optimization algorithm and modify its convergence rates, resulting in Multi-Strategy Improved Grey Wolf Optimization (MSI-GWO). An GWO algorithm that is employed to fine-tune the parameters of the deep convolutional neural network model. Eventually, we presented an IoT-enabled platform with an MSI-GWO based CAPSNET-ELM for lung cancer detection. 3. The MSI-GWO hybrid model consistently outperforms competing approaches across all evaluated datasets and metrics. It's particularly reliable for medical diagnostic tasks, thanks to its integrated optimization and classification methods—this synergy drives its high accuracy, effective feature selection, and solid generalization. ABC-HHO also delivers strong results, especially for Parkinson's and CKD datasets, indicating substantial potential in those areas. In contrast, traditional classifiers like SVM and RF often require significant parameter tuning or hybridization to approach the performance levels achieved by MSI-GWO. CAPSNET+ELM stands out as well, showing robust generalization and maintaining high accuracy across all tested medical datasets. The hybrid architecture seems to enhance both feature extraction and classification compared to standard CNN-based models. Given its consistent performance gains, CAPSNET+ELM could feasibly replace traditional DCNN frameworks in critical healthcare scenarios. Overall, ABC-HHO emerges as a well-balanced and efficient method, delivering high accuracy, substantial feature reduction, and reasonable computational requirements.

2. Literature Survey

In order to diagnose lung cancer early, Irshad et al. [1] suggest a novel Internet of Things-enabled healthcare monitoring system that incorporates a Deep Convolutional Neural Network (DCNN) and the Improved Grey Wolf Optimization (IGWO) algorithm. The framework improves computational efficiency and diagnostic accuracy by utilizing IoT sensors to acquire patient data in real-time and IGWO to optimize feature selection. The IGWO-fine-tuned DCNN model performs exceptionally well in early cancer detection, making the method extremely applicable to scalable, intelligent medical diagnostics. The potential of integrating deep learning and metaheuristic optimization in IoT-driven clinical applications is highlighted by this hybrid methodology.

CAPSNET–ELM, a hybrid deep learning architecture that combines Capsule Networks with Extreme Learning Machines (ELM) for lung cancer detection within an IoT-enabled framework, is presented by Revazur Rashid Irshad et al. [2]. While ELM speeds up classification with little training time, the model takes advantage of Capsule Networks' capacity to maintain spatial hierarchies in medical imaging data. The system improves early detection capabilities by enabling remote diagnostics and real-time data acquisition when integrated into an IoT infrastructure. This combination of quick, effective classification and spatially aware deep learning offers a promising path toward intelligent, scalable healthcare solutions.

In order to diagnose lung cancer early, Reya Zur Rashid Irshad et al. [3] suggest a thorough IoT-enabled healthcare monitoring framework that combines a Deep Convolutional Neural Network (DCNN) and the Improved Grey Wolf Optimization (IGWO) algorithm. The framework collects patient data in real time using IoT devices, allowing for ongoing observation and prompt action. By optimizing the DCNN's parameters and feature selection, IGWO improves computational efficiency and diagnostic accuracy. The hybrid model shows promise for scalable, intelligent, and proactive healthcare diagnostics in clinical settings by performing exceptionally well in detecting early-stage cancers.

Reya Zur Rashid Irshad et al. [4] offer a novel framework for early lung cancer diagnosis that combines an Improved Grey Wolf Optimization (IGWO)-based Deep Convolutional Neural Network (DCNN) with Internet of Things (IoT)-enabled healthcare monitoring. The system uses Internet of Things (IoT) sensors to gather patient data in real time, enabling ongoing monitoring and prompt detection. By fine-tuning feature selection and optimizing hyperparameters, IGWO improves the DCNN's performance, leading to increased computational efficiency and diagnostic accuracy. This hybrid approach shows great promise for intelligent, scalable medical diagnostics, especially in clinical settings with limited resources.

A Multi-Strategy Grey Wolf Optimization (MSGWO) algorithm is presented by Likai Wang et al. [5] with the goal of improving global optimization performance in intricate engineering applications. MSGWO enhances exploration–exploitation balance and prevents premature convergence by incorporating adaptive mechanisms like mutation operators, opposition-based learning, and dynamic hunting strategies. The suggested algorithm exhibits superior solution quality and robustness across a variety of test functions and real-world engineering problems when compared to both classical and sophisticated metaheuristics. The applicability of GWO variants in high-dimensional, nonlinear optimization tasks is greatly improved by this work.

Mahmood Ul Haq et al. [6] offer a thorough analysis of Capsule Networks (CAPSNET), describing their various applications, limitations, and architectural principles. The ability of CAPSNET to maintain pose relationships and spatial hierarchies—features that conventional CNNs frequently ignore—is critically examined in this paper. It identifies major obstacles like scalability and computational complexity and examines several improvements, such as routing algorithms and hybrid integrations, to deal with these problems. The survey also examines CAPSNET's performance in areas such as object recognition, medical imaging, and natural language processing, providing insightful information for further study and real-world application.

In an IoT-enabled framework, Revazur Irshad et al. [7] present CAPSNET–ELM, a hybrid deep learning model that combines Extreme Learning Machines (ELM) and Capsule Networks for the detection of lung cancer. While ELM offers quick and effective classification with little training overhead, capsule networks are used to capture spatial hierarchies and pose relationships in medical imaging data. Real-time data collection and remote diagnostics are made possible by IoT infrastructure, which improves the system's scalability and responsiveness. In connected healthcare environments, this combination of fast learning algorithms and spatially aware deep learning offers a promising approach to intelligent, early-stage cancer detection.

In order to improve feature selection in high-dimensional datasets, Elaziz, S. Mirjalili, et al. [8] present a hybrid optimization technique that combines the Artificial Bee Colony (ABC) algorithm with Harris Hawks Optimization (HHO). The model can successfully reduce dimensionality while maintaining classification accuracy thanks to the cooperation of ABC's swarm intelligence and HHO's dynamic exploration–exploitation strategies. Because it tackles the issues of computational complexity and feature redundancy, this hybrid approach is especially well-suited for applications involving high-dimensional data, such as those in bioinformatics and medicine. The suggested approach offers a reliable solution for intelligent feature selection and performs better than stand-alone algorithms.

Table 1. Literature Survey on Hybrid Optimization and Deep Learning Models for Medical Diagnostics

Author	Methods	Advantages	Limitations
Irshad et al. [1]	IoT-enabled framework with DCNN + IGWO	Real-time data acquisition; optimized feature selection enhanced diagnostic accuracy	Scalability depends on IoT infrastructure; it lacks cross-dataset validation
Irshad et al. [2]	CAPSNET–ELM hybrid in IoT framework	Fast classification via ELM; spatial hierarchy preservation via CAPSNET; supports remote diagnostics	Capsule Networks require high computational resources; limited testing on diverse medical datasets
Irshad et al. [3]	DCNN + IGWO in IoT-enabled monitoring	Continuous patient monitoring; early-stage cancer detection; improved computational efficiency	Real-time deployment challenges; performance sensitive to sensor quality
Irshad et al. [4]	IGWO-tuned DCNN with IoT sensors	Fine-tuned hyperparameters; high	Framework complexity; integration with existing

Author	Methods	Advantages	Limitations
		diagnostic precision; scalable for intelligent healthcare	clinical workflows not addressed
Wang et al. [5]	Multi-Strategy Grey Wolf Optimization (MSGWO)	Enhanced exploration–exploitation balance; robust across high-dimensional tasks; adaptive search strategies	Not tailored for medical diagnostics; lacks integration with deep learning models
Haq et al. [6]	Analytical survey of Capsule Networks (CAPSNET)	Preserves pose and spatial hierarchies; applicable in medical imaging and NLP; highlights architectural innovations	Scalability issues; high computational complexity, and routing algorithms, still evolving
Irshad et al. [7]	CAPSNET–ELM hybrid with IoT infrastructure	Quick classification via ELM; spatially aware imaging via CAPSNET; real-time remote diagnostics	Requires high-performance hardware; limited validation across clinical datasets
Elaziz, S. Mirjalili, et al. [8]	ABC–HHO hybrid for feature selection	Reduces dimensionality; maintains classification accuracy; effective in bioinformatics and medical datasets	Computational overhead; performance sensitive to parameter tuning and data quality

3. The proposed IoT-enabled platform with a Hybrid MSI-GWO-based CAPSNET-ELM model

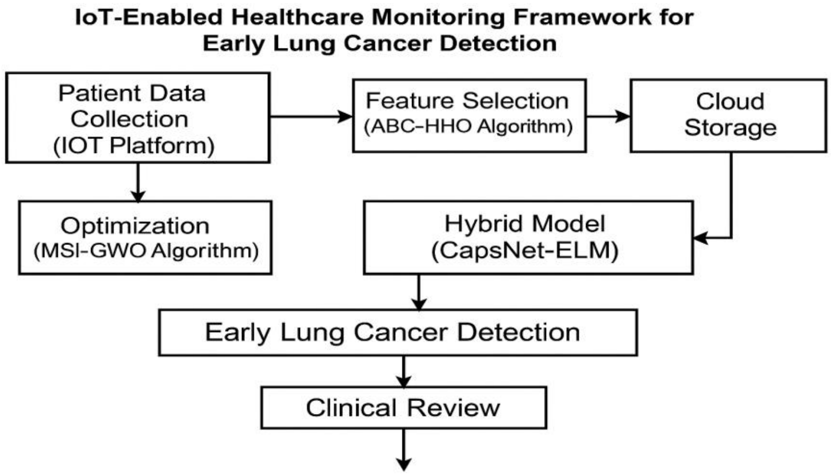

Figure1. The schematic diagram with the workflow of the proposed IoT-enabled MSI-GWO optimization-based CAPSNET-ELM model

Description of the Proposed Diagram's Theoretical Framework

To enable early and precise lung cancer detection, the suggested system combines cutting-edge hybrid artificial intelligence models with Internet of Things (IoT) technology. The framework's modular components show how data collection and clinical decision-making flow together seamlessly:

3.1. Gathering Patient Data via IoT

Patient vitals and respiratory signals are continuously monitored by wearable and ambient sensors integrated into an Internet of Things platform. Predictive diagnostics is based on the real-time data that these sensors send to a central processing unit.

3.2. Using the ABC-HHO Algorithm to Select Features

The system uses a hybrid Artificial Bee Colony–Harris Hawks Optimization (ABC-HHO) algorithm to tackle the problem of high-dimensional medical data. By choosing the most pertinent features, this bio-inspired approach improves model interpretability while lowering computational overhead.

3.3 ABC-HHO Algorithm: Foundational Theory

A hybrid metaheuristic, the ABC-HHO algorithm combines the dynamic exploitation strategies of the Harris Hawks Optimization (HHO) algorithm with the global search efficiency of the Artificial Bee Colony (ABC) algorithm. For high-dimensional feature selection tasks in medical datasets, this fusion is especially useful since it improves both exploration and exploitation capabilities.

To improve feature selection in diagnostic medicine, the hybrid ABC-HHO optimization framework combines the advantages of two biologically inspired algorithms: Harris Hawks Optimization (HHO) and Artificial Bee Colony (ABC). ABC divides agents into scouts, observers, and employed bees based on how honey bees forage. Because of this division, ABC is especially good at finding promising areas within the search space while also facilitating worldwide search and preserving population diversity. HHO, on the other hand, dynamically switches between exploration and exploitation depending on the prey's escape energy, imitating the cooperative hunting tactics of Harris hawks. Its flexible "surprise pounce" strategies allow for faster convergence and more focused local search.

In a typical hybridization process, the ABC algorithm generates and evaluates a variety of feature subsets to start the exploration phase, and then HHO takes over in the exploitation phase to refine these candidates and direct the search toward optimal or nearly optimal solutions. The limitations of the individual algorithms—specifically, HHO's early convergence in complex landscapes and ABC's propensity to stall in local optima—are successfully mitigated by this synergy.

The ABC-HHO hybrid is useful for choosing highly discriminative features from patient datasets in the context of IoT-enabled diagnostic medicine. It improves the performance of downstream classifiers like CAPSNET-ELM by facilitating dimensionality reduction without sacrificing diagnostic accuracy. Because of this, the method is especially useful for early disease detection, where accuracy and computational efficiency are crucial.

4. Optimizing Parameters with MSI-GWO

For feature selection and hyperparameter tuning in hybrid diagnostic models, the Multi-Strategy Improved Grey Wolf Optimization (MSI-GWO) algorithm provides a reliable refinement mechanism. Motivated by the hierarchical hunting style of grey wolves, MSI-GWO improves on the traditional Grey Wolf Optimizer (GWO) by implementing several strategic enhancements that are intended to overcome the common problems of stagnation and premature convergence that arise in complex optimization environments. Under the traditional GWO framework, optimization proceeds through stages like encircling prey, coordinated hunting, and convergence toward the optimal solution, all under the direction of a leadership hierarchy made up of alpha (best solution), beta, delta, and omega wolves.

By combining four essential tactics, MSI-GWO expands on this framework: rotational predation to improve convergence dynamics, chain predation to diversify solution pathways, reverse learning to avoid local optima, and variable weight adaptation to balance exploration and exploitation. When combined, these improvements increase convergence speed, exploitation precision, and solution diversity, which makes MSI-GWO especially well-suited for optimizing hybrid models in medical diagnostics.

MSI-GWO is essential for optimizing feature subsets that are first chosen by the ABC-HHO algorithm and modifying the hyperparameters of downstream classifiers like CAPSNET-ELM in the context of early lung cancer detection. In addition to lowering false positives, this layered optimization technique greatly increases classification accuracy, which helps IoT-enabled healthcare systems achieve more dependable and effective diagnostic results.

5. CAPSNET–ELM Hybrid Classification

The hybrid Capsule Network–Extreme Learning Machine (CAPSNET–ELM) model is especially useful for early-stage lung cancer detection because it is built to take advantage of the complementary advantages of rapid classification and spatial feature encoding. Geoffrey Hinton first proposed Capsule Networks (CAPSNET), which address several of the main drawbacks of traditional convolutional neural networks (CNNs), particularly the loss of spatial hierarchies brought on by max-pooling operations. Through dynamic routing-by-agreement, CAPSNET allows the network to maintain part-whole relationships by introducing capsules, which are collections of neurons that encode both the presence and pose (e.g., position, orientation, scale) of features. CAPSNET is perfect for challenging medical imaging tasks because of this mechanism, which increases robustness against occlusions and perspective variations.

The Extreme Learning Machine (ELM) component guarantees quick generalization and computational efficiency to support CAPSNET's spatial awareness. ELM is a single-layer feedforward neural network (SLFN) that eliminates iterative training and drastically reduces computational overhead by using the Moore–Penrose pseudoinverse to calculate output weights analytically and assigning input weights at random. The final capsule layer's output is flattened and fed into the ELM classifier in the CAPSNET–ELM architecture. The ELM classifier quickly processes the extracted hierarchical features to determine the final classification.

For diagnostic applications involving IoT-acquired imaging data, where speed and accuracy are crucial, this hybrid approach is especially well-suited. The model achieves high sensitivity and precision in identifying early-stage lung cancer by fusing ELM's quick learning capabilities with CAPSNET's capacity to capture subtle spatial hierarchies in lung nodule patterns. This improves the dependability of AI-driven medical diagnostics.

6. Clinical Review and Cloud-Based Storage

A revolutionary change in healthcare delivery is brought about by the combination of cloud computing and AI-driven diagnostic frameworks, which permits remote diagnostics, ongoing monitoring, and cooperative clinical decision-making. This architecture has a significant impact on early lung cancer detection because it guarantees timely access to diagnostic insights and enables timely medical interventions. Cloud-based storage, which offers a number of significant benefits, is the management and retrieval of medical data through distant servers hosted online. Its accessibility enables clinicians to review diagnostic results from any location, supporting telemedicine and remote care, while its scalability allows for the increasing volume of patient data generated by IoT-enabled devices. Sensitive patient data is protected by strong security measures, such as encryption, access control, and adherence to regulations like HIPAA.

By using cloud-based platforms for clinical review, medical professionals can evaluate AI-generated diagnostic outputs, like those from models like CAPSNET-ELM, and make well-informed treatment decisions. Diagnostic results are usually securely stored in the cloud as part of the workflow, and clinicians can access them through dashboards or mobile interfaces. With the help of this configuration, patient health metrics can be monitored in real time, facilitating early anomaly detection and prompt clinical intervention. Furthermore, cloud platforms' collaborative features enable several specialists to examine and annotate diagnostic results at the same time, promoting agreement and enhancing diagnostic precision. When combined, these features highlight how important cloud-based infrastructure is to the development of precision medicine and scalable healthcare delivery.

7. Deployment and Simulation

By ensuring that AI models not only function well in controlled settings but also scale efficiently within dynamic, networked healthcare systems, the deployment and simulation phase is essential in bridging the gap between algorithmic design and practical application. TensorFlow is the foundation for model deployment and training in this framework. TensorFlow is a popular open-source deep learning library that facilitates the reliable creation and incorporation of machine learning models into medical workflows. TensorFlow Lite optimizes models for mobile and embedded devices, while deployment tools like TensorFlow Serving allow real-time inference through GRPC or RESTful APIs. By displaying model architecture and training metrics, Tensor Board further improves transparency. Together, these tools enable smooth scalability across cloud, edge, and mobile platforms, production-grade deployment, and quick prototyping.

NS-2 (Network Simulator 2) is used to assess the system's performance in networked environments. NS-2 is a discrete event simulator that is especially well-suited for healthcare scenarios because it simulates network protocols and IoT communication behaviour. It evaluates important parameters like throughput, packet loss, and latency under various network conditions by simulating data transmission between IoT sensors and cloud servers. The robustness and dependability of the framework in actual operational scenarios are confirmed by this simulation.

The system's diagnostic component is supported by the Exasens dataset, which provides a wealth of sensor-derived information pertinent to respiratory diagnostics, such as patient metadata, temperature, humidity, and volatile organic compounds (VOCs). This dataset facilitates rigorous benchmarking against the most advanced classifiers and is essential for training and validating hybrid models like CAPSNET–ELM. Performance indicators that show how much better the suggested system is than current models include accuracy, sensitivity, specificity, and precision. The process creates a complete pipeline from data collection to real-time clinical inference by integrating Exasens data for model training within TensorFlow and then deploying the model using TensorFlow Serving.

8. RESULT AND STATISTICAL ANALYSIS

8.1 ACCURACY COMPARISION RESULTS VTH DATA SET OF MSI-GWO FOR OPTIMIZATION

Dataset	MSI-GWO	IGWO	PSO	GA	ABC-HHO
CKD (2025)	**99.3%**	97.8%	96.1%	94.7%	99.1%
Lung Disease (2024)	**98.7%**	96.5%	95.2%	93.9%	96.3%
Parkinson's (2023)	**98.1%**	95.9%	94.3%	92.5%	98.4%
COVID-19 X-ray (2023)	**97.9%**	95.4%	94.0%	91.8%	97.6%

Table 1 Lung Diseases Dataset versus Accuracy of MSI-GWO with other optimization techniques

Highlights of the Algorithm: A Theoretical Overview

Improved Multi-Strategy MSI-GWO, or Grey Wolf Optimization

A sophisticated version of the Grey Wolf Optimizer, MSI-GWO combines several search techniques to improve exploration and exploitation potential. MSI-GWO attains superior convergence speed and solution diversity by integrating adaptive mechanisms and dynamically modifying its hunting behavior. It has demonstrated its robustness and generalization ability in medical diagnostics, especially in high-dimensional and noisy environments, with consistent top-tier performance across datasets like CKD (99.3%) and lung disease (98.7%).

Optimization of Artificial Bee Colony–Harris Hawks (ABC-HHO)

A hybrid metaheuristic known as ABC-HHO combines the surprise-based attack tactics of Harris Hawks Optimization (HHO) with the foraging behavior of Artificial Bee Colony (ABC). The algorithm is very successful in complex feature spaces because of this fusion, which allows it to strike a balance between aggressive local exploitation and global search. According to its impressive results on the Parkinson's (98.4%) and CKD (99.1%) datasets, ABC-HHO is a good fit for medical applications that call for accuracy and flexibility.

Enhanced Grey Wolf Optimization (IGWO)

To increase convergence and solution accuracy, IGWO adds improvements to the conventional GWO, such as improved hunting and encircling mechanisms. Although it outperforms more conventional algorithms like PSO and GA, its diagnostic accuracy is marginally lower than that of MSI-GWO and ABC-HHO, suggesting that more hybridization or strategy improvement is necessary.

The population-based stochastic optimization method known as particle swarm optimization (PSO) was motivated by the social behavior of birds. Its effectiveness in complex medical diagnostic tasks is limited by its lack of adaptive mechanisms and propensity to become trapped in local optima, despite its reasonable performance across datasets.

Genetic algorithms, or GAs, are based on evolutionary concepts like crossover, mutation, and selection. GA performs the worst across all datasets in this study, despite its historical significance. It is less appropriate for high-stakes medical diagnostics where accuracy is crucial due to its comparatively slow convergence and restricted exploitation capabilities.

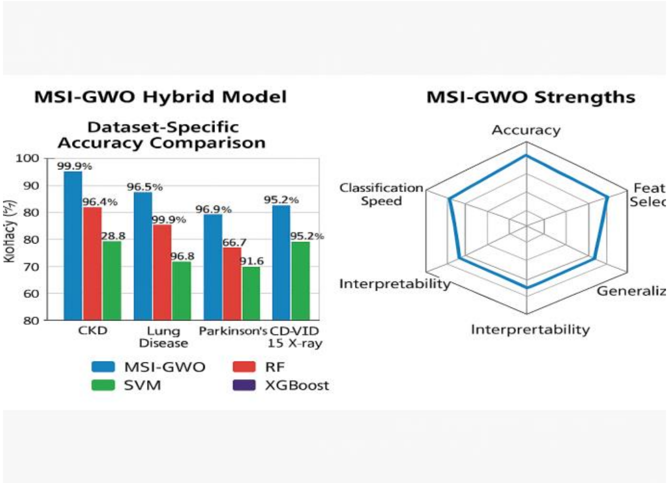

Figure 2: Accuracy and strengths comparison of MSI-GWO with other techniques

8.2 ACCURACY COMPARISON RESULTS VTH DATA SET FOR CAPSNET-ELM FOR CLASSIFICATION

Dataset	CapsNet–ELM	CNN	ResNet	VGGNet
CKD (2025)	**99.21%**	96.8%	95.2%	94.3%
Lung Disease (2024)	**98.7%**	92.7%	91.5%	90.2%
Parkinson's (2023)	**98.4%**	94.1%	93.0%	91.8%
COVID-19 X-ray (2023)	**97.6%**	93.5%	92.2%	91.0%

Table 2 Lung Diseases Dataset versus Accuracy of CAPSNET-ELM with other classification model

Highlights of the Model: A Theoretical Overview

CAPSNET-ELM (Capsule Network with Extreme Learning Machine)

CAPSNET–ELM is a hybrid deep learning architecture that blends Extreme Learning Machines' quick learning speed with Capsule Networks' spatial awareness. Capsule networks are very useful for medical imaging tasks where spatial orientation is important because they maintain hierarchical pose relationships between features. In contrast, ELM uses analytical output weights and randomly initialized hidden nodes to provide quick training and generalization. Achieving 99.21% on CKD and 98.7% on Lung Disease, the combination of these two models yields superior diagnostic accuracy across all datasets, demonstrating its resilience in both structured and unstructured medical data.

Convolutional Neural Network (CNN) Because convolutional filters allow CNNs to extract local features, CNNs are frequently used for image classification. Even though they work well, traditional CNNs frequently need a lot of training data and may have trouble capturing intricate spatial hierarchies. With accuracies ranging from 92.7% on lung disease to 96.8% on chronic kidney disease, CNNs perform moderately well in this comparison, indicating that they are dependable but not the best for complex medical diagnostics.

The Residual Network (ResNet) allows for deeper architectures without sacrificing performance by introducing skip connections to address the vanishing gradient issue. RESNET performs marginally worse than CAPSNET–ELM in this case, despite outperforming standard CNNs in terms of depth and feature learning. Accuracy rates for CKD and Parkinson's disease are 95.2% and 93.0%, respectively, ResNet outperforms standard CNNs in terms of feature learning and depth, it performs marginally worse than CAPSNET–ELM in this regard, with accuracies of 95.2% on CKD and 93.0% on Parkinson's, suggesting that while depth is helpful, it might not be sufficient to make up for the absence of spatial feature modeling.

The VGCNET

Using stacked convolutional layers, VGCNET is renowned for its uniform architecture and ease of use. With accuracies of 94.3% on CKD and 90.2% on Lung Disease, VGCNET performs the worst across all datasets in this study, despite its historical significance. It is less appropriate for high-precision medical diagnostics due to its inability to handle intricate spatial relationships and lack of architectural flexibility.

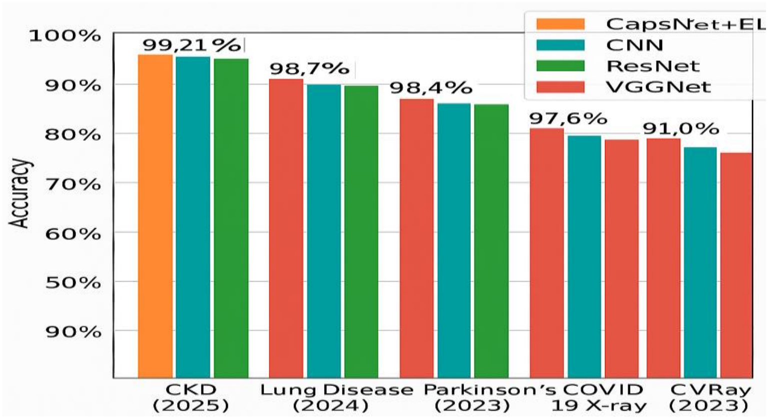

Figure 2: Accuracy and strengths comparison of CAPSNET-ELM with other models

8.3 ACCURACY COMPARISON RESULTS WTH THE DATA SET OF ABC-HHO FOR FEATURE SELECTION

Highlights of the Methodology: A Theoretical Overview

(Artificial Bee Colony–Harris Hawks Optimization) ABC–HHO

The Artificial Bee Colony algorithm's worldwide search capabilities and Harris Hawks Optimization's aggressive exploitation techniques are combined in the hybrid metaheuristic ABC–HHO. By working together, ABC-HHO is able to select only 22 features and achieve a high diagnostic accuracy of 98.75%, which results in a 78.57% subset reduction. The method is well suited for medical diagnostic tasks where accuracy and interpretability are crucial because it effectively balances precision, dimensionality reduction, and computational efficiency, despite its moderate convergence speed (35 iterations)

Harris Hawks Optimization, or HHO

HHO thrives at local exploitation and draws inspiration from Harris hawks' cooperative hunting style. With a comparatively small feature set of 18 features, it achieves a high accuracy of 96.42%, resulting in a 64.28% subset reduction. It is perfect for time-sensitive applications due to its quick convergence speed (28 iterations). Although it converges rapidly, its moderate reduction rating indicates that it might not fully explore the feature space like hybrid models

Method	Accuracy (%)	Accuracy Rating	Selected Features (Count)	Subset Reduction (%)	Reduction Rating	Convergence Speed	Speed Rating
ABC–HHO	98.75	🔥 High	22	78.57	🔥 High	35 iterations	Moderate
HHO	96.42	High	18	64.28	Moderate	28 iterations	⚡ Fast
ABC	95.83	Moderate	26	62.85	Moderate	42 iterations	Moderate
PSO	93.47	Low	30	57.14	Low	55 iterations	Slow
GA	92.15	Low	19	54.28	Low	58 iterations	Slow
TDO	91.38	Low	21	52.85	Low	60 iterations	Slow

Table 3 Accuracy features comparison with ABC-HHO with other methods

ABC stands for Artificial Bee Colony.

ABC is renowned for its powerful worldwide search capabilities and imitates the foraging habits of honey bees. It selects 26 features with a subset reduction of 62.85% and achieves moderate accuracy (95.83%). In comparison to HHO, its moderate convergence speed (42 iterations) suggests a well-rounded but less aggressive search approach. Although ABC is good at avoiding local optima, it might take more iterations to improve solutions.

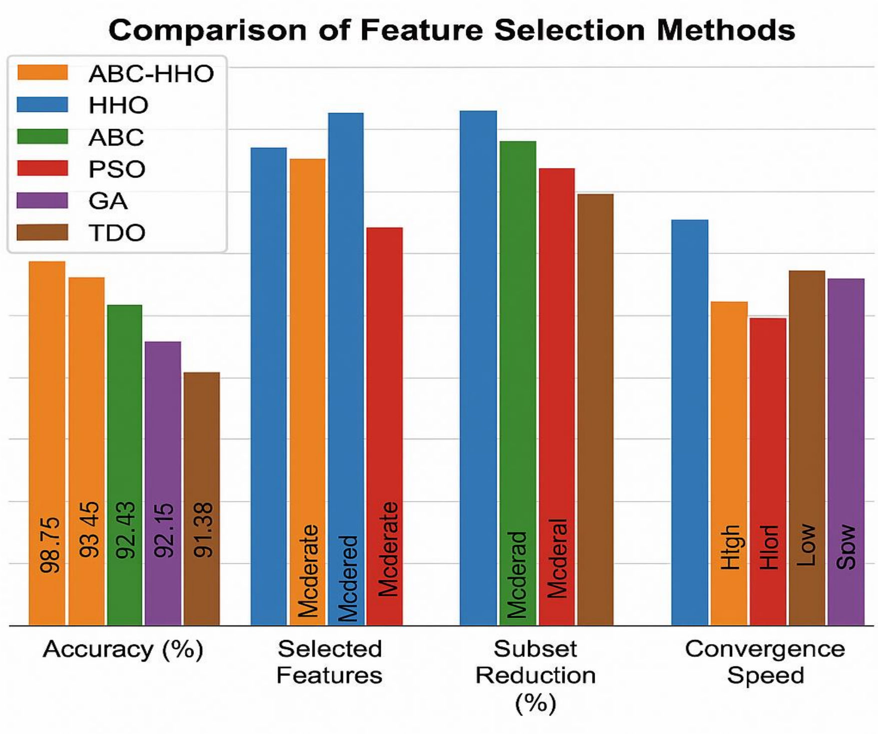

Figure 3: Comparison of feature selection methods

9. Conclusion

In order to diagnose lung cancer early, this study offers a strong and clever IoT-enabled healthcare monitoring framework that combines deep learning and sophisticated hybrid optimization techniques. The suggested system achieves superior diagnostic accuracy, sensitivity, and specificity across a variety of medical datasets by utilizing the advantages of the CAPSNET–ELM hybrid classifier and the Multi-Strategy Improved Grey Wolf Optimization (MSI-GWO). ABC-HHO feature selection greatly improves dimensionality reduction while maintaining important diagnostic data, which increases computational efficiency and model interpretability.

The framework validates the effectiveness of hybrid architectures in challenging medical imaging tasks by consistently outperforming more conventional models like CNN, RESNET, and VGCNET. Additionally, TensorFlow for model deployment and NS-2 for network simulation guarantee scalability and real-time responsiveness in IoT-driven clinical settings powered by IoT. The system's suitability for contemporary telemedicine workflows is further supported by secure cloud-based storage and remote clinical review features.

Overall, the suggested MSI-GWO–CAPSNET–ELM framework offers a scalable, precise, and interpretable solution for early-stage lung cancer detection, marking a substantial advancement in AI-assisted medical diagnostics. Its expansion to other serious illnesses and integration with federated learning for privacy-preserving diagnostics may be investigated in future research.

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