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Enhancing Lung Cancer Detection with Hybrid Machine Learning: Integrating Ant Colony Optimization

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Abstract- Lung cancer is still ranked among the major killers and current techniques used in the diagnosis of this condition do not assist in early detection. In this paper, research seeks to work towards resolving the early detection of lung cancer using ACO and more specifically, the hybrid learning models. The ACO optimization algorithm based on foraging ants is used to select the features that contributes to model simplification and increased performance. The developed approach incorporates ACO with DNN in order to enhance the diagnostic performance of the system. The performance of the proposed approach has been evaluated and analyzed for different scenarios using experimental results, it has been shown that the accuracy of the DNN model is relatively increased and achieved up to 0. 91 to 0. 97 that indicates that application of ACO in breast cancer detection has the ability of minimizing false positives and thus improving the chances of early diagnosis. This line of work is a major advance towards more accurate diagnosis of lung cancer, and can be extrapolated to the field of more targeted health care.

Keywords- Deep Learning, Ant Colony Optimization (ACO), Lungs Cancer, DNN, ML

I. Introduction

Lung cancer has remained one of the leading causes of morbidity and mortality among people with cancer in the world and is responsible for about 1. 8 million deaths annually. Screening for Lung cancer is very important to increase the number of patients who live; for the 5 years survival rate is high when the lung cancer has not reached the advanced stages of the ailment. However, current diagnostic techniques include imaging methods like, chest X and CT scans which do not diagnose the disease in its early stage primarily due to the inability to differentiate between benign and malignant neoplasms. It is important to note that while the invasive techniques such as biopsies are more precise compared to the other methods when it comes to accuracy and therefore used in the early detection, they are complicated time consuming and pose considerable risks to the patients' lives hence are rationed in their use.

Machine learning is one of the potential technologies that allows using big datasets and identify possible relations which are hard for a human to discern. Some work has been done in using the ML models in diagnosing lung cancer, but the methods are limited by issues to do with feature selection. A large dataset in a feature space of high dimensionality is prone to overfitting whereby the model's accuracy in the training data is high but does not reflect on new data. In addition, unnecessary characteristics, that with high probability do not influence the process, raise the number of false positive diagnoses.

Ant Colony Optimization (ACO), an optimization method mimicking the ants foraging behavior, seems to hold the key to feature selection issue. ACO is also good at performing a structured search for the feature space when searching for the most relevant features and at the same time providing the method to reduce dimensionality. This way, ACO tries to enhance the aspect of key features to enhance the accuracy of the machine learning process and its ability to generalize in higher dimensions, which is especially needed when dealing with extended medical data such as the lung cancer detection data set. In this work, we are planning to incorporate ACO with Deep Neural Networks (DNN) to minimize the parameter's complexity and the variability of feature space to get better lung cancer detection with more accuracy.

Over the past few years, ML has proven to be a hugely valuable option for diagnosing diseases including lung cancer, and has a vast capacity to radically transform the practice. Due to their ability in the large-scale data analysis and pattern recognition, the applications of the ML algorithms have become more common in the classification and diagnosis of diverse cancer types, including lung cancer[2-3]. They can also accept numerous forms of input data including images, patients' information and even genetic data and come up with precise diagnosis. Nevertheless, prospective researches have now demonstrated possible values of achieving greater diagnostic accuracy using different ML models. One of the major problems of employing ML within lung cancer detection is feature selection—finding out which of the many variables or features contained in the data offered are helpful for yielding accurate predictions[4-5]. Very often, due to the large number of variables and the existence of noise factors or more generally, redundant attributes, the model becomes overly complex and subject to overfitting, high accuracy on the training set but low accuracy on new data. This has posed the challenge to researchers to seek for a middle ground, between ML and other optimization methods that will improve the model.

One of such optimization techniques is Ant Colony Optimization (ACO), which is a metaheuristic based on the food searching behavior of ants. ACO has largely been adopted over the years to efficiently solve CSPs and especially feature selection in developing robust ML models. The integration of ACO with ML algorithms presents a potential direction of enhancing the performance of the lung cancer detection models. Just like the ants that look for the shortest and quickest way to get to the food source, ACO does an excellent job in determining what are important features in the data, thereby making the dimensionality reduction technique make the model to improve on how it handles unseen data[6]. Besides the problem of overfitting, this approach also considers the practicality of the diagnostic model, especially when implemented on a computer. The rationale for this work comes from the fact that this mixed strategy offers a significant opportunity for elaborating the gap between theory in ML and its implementation in the health-care sector[7-8]. This study intends to combine the strengths of both ML and ACO in an attempt to design a more precise, credible, and effective tool for early lung cancer detection so as to improve patients' survival rates and promote the progress of medical diagnosis tools.

Lung cancer especially if it is detected early is easily treatable hence the importance of early detection as a way of enhancing the patient outcome. Lung cancer is often symptomless at an initial phase and most patients present with a history of treatment only after the disease has reached an advanced stage making the intervention and treatment much harder and less likely to produce a good outcome. Research also indicated that in the instance where the disease is diagnosed at an early stage; the five-year survival rate could be at 56% against an overall of 5% in the case of late-stage lung cancer[7], [9]. This contrast underlines the need for the identification of sound and effective mechanisms for the early diagnosis of the signs. The conventional procedures that are used in diagnosing the disease that include chest X-rays, CT scans, and biopsies while common do not enhance early diagnosis because of the following challenges. For example, in imaging methods some tumors appear benign while in actual they are malignant thereby giving either a false positive of a false negative result. Further, some lump biopsies are accurate but are invasive and involves likelihood of some danger hence they cannot be as commonly used in screening methods as the mammogram[9]. We are presented with these challenges today which call for more enhanced diagnosis for lung cancer in the early stage with high sensitivity and specificity while at the same time exercising minimum invasiveness.

The push for early detection is not the sole focus on extending the people's survival; it also leads to savings on the cost of healthcare and the enhancement of people's wellbeing. The first-line therapy for stage I lung cancer is less destructive than the therapies for stage III and IV cancers and, consequently, is cheaper and less likely to have severe consequences, including death. Early detection also implies that patients can avoid more aggressive treatment methods, thus improving on the quality of life because they are not constantly in pain. For such reasons, efforts are currently being made on screening programs and diagnostic procedures to locate and diagnose lung cancer at the earliest stages possible so that the prognosis of the patient may be improved[10].

Medical diagnosis has also benefited from the implementation of the various principles of ML; it has brought new ways of developing better diagnostic models of diseases such as lung cancer. Machine Learning techniques includes the process of learning from data and also the process of making decisions based on data. In the context of diagnosis, then, ML models are built off of patient information such as images, genotypes, or records and then learn correlations which might not be openly seen to a clinical expert[11]. They can make predictions about the possibility of diseases, identify risk factors and even recommended a course of treatment. The use of ML in the diagnosis of medical conditions has been on the rise in the past few years, due to improvements in technology, increase in investment in health care data and creation of complex algorithms.

Various techniques of ML have been employed effectively in lung cancer detection and sharing certain advantages and vice versa. For example, Support Vector Machines (SVM) are very popular due to their capability to categorize data into two or more sets and are therefore suitable for use in separating tumors that are malignant and those that are benign. Deep learning such as CNNs is most useful in the processing and analysis of different types of medical images; more particularly, CT scans in ascertaining the probability of lung cancer based on depicted abnormality[12], [13]. Another set of frequently used ML technique is Random Forests They are well known due to their high level of insensitivity to the number of features and the size of the dataset. Each of these techniques has been found, when used alone, to yield more accurate diagnoses. However, the confronting factors of Lung cancer are its gradual penetration and its multiformity, it may present differently and initial signs and symptoms can be almost invisible, compared to other diseases Lung cancer is a much more complicated issue, and it usually needs more specific intervention because of its versatility.

But this is the case where the combination of ML with other computational methods like optimization algorithms is valuable. As a result, in the field of diagnosis associated with many difficulties and insufficiencies as lung cancer, the integration of the load of machine learning and optimization methods including Ant Colony Optimization (ACO) can develop the efficiency of diagnostic models and increase the stability of the models. The cooperation of ML and optimization methods hence contributes to the enhanced feature learning, improved model predictability, and better lung Cancer early diagnosis[14-15]. In the future, this function will continue to develop and expand the use of Machine Learning in the attractive and creative application of diagnostic healthcare. Machine learning/Multiple algorithms/Complex fields:

Hybrid models In Machine learning, multiple techniques or more than one algorithm can be used together to develop the best output or the best prediction to the problem at hand especially in potentially difficult areas such as medical diagnosis. The basis of hybrid models is in the assumption that by in reconnecting two or more methods, the over al powered model is free from some of the inherent deficiencies of any of the component algorithms[16-17]. It is thus fitting to consider hybrid models as a way of enhancing lung cancer detection, given the high risk involved and the potential benefits that can be obtained in the process. These models can combine methods from machine learning including Support Vector Machines (SVM), Random Forests, as well as Neural Networks with, for instance, Ant Colony Optimization (ACO), in efforts to alleviate the problem.

The strengths of hybrid models can be bests seen in the potential to solve several critical issues in lung cancer diagnosis. There are a few challenges inherent in this domain, one of the main of which is a feature selection, which is aimed at finding the most valuable variables that determine high accuracy of predictions. Depending on the type of the employed ML model, feature selection might prove difficult, especially when working with large datasets containing many features that have no significant impact on the result[18]. This may result in over-fitting of the model where the model is very good at performing on the training data but very poor on unseen data. Hybrid models by integrating a machine learning algorithm with an optimization technique such as used in ACO is able to cope with this complexity. ACO is all about developing a near-optimal solution in the large search space as ants do when they go foraging. When used in feature selection, it can search through the data systematically to find out the best feature set of describing the data and then eliminate the rest of the noise features, thus resulting in improved model generalization.

In addition to the issue of feature selection, where the effectiveness of the proposed hybrid approaches is quite significant, the hybrid models are also far superior to other aspects of determining lung cancer presence. For instance, it can improve the interpretability of the model; thus, clinicians will easily understand the basis of the predictions made. This is especially the case in healthcare since change in the technology requires patients' trust and information sharing[19]. Furthermore, the hybrid models can enhance the computational speed and give higher modality for the diagnostic process. This is done based on the balance between the complexity of the models the accuracy to mean that the model that is produced is accurate but at the same time realistic in the modern world. In identifying lung cancer, where the differentiation between an early-stage disease and a terminal one may lie, it is a lifesaver to be able to employ an effective model in practice.

The shift to both hybrid models of lung cancer identification remain limited but the usage has already revealed its advantages. Such models have been demonstrated to offer a higher performance than traditional machine learning techniques in respect of, inter alia, accuracy and stability. Thus, as investigative work in this field progresses, integration of elements of the chosen types of models will only increase importance in medical diagnosis[20]. They provide a way to more accurate and individualized approach to healthcare, in which the specificity of numerous patient's data can be used to a greater extent. While most existing methods are based on a single technique, the combination of several of them into a single model makes hybrid approaches able to change the diagnostics and treatment of diseases such as lung cancer and improve the quality of patients' lives.

Problem Statement

Huge progress in machine learning as well as in diagnosis of human diseases did not make early

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detection of lung cancer easier; it remains an unsolved problem due to the heterogeneity of the disease. Routine diagnostic techniques frequently fail to provide reliable results especially at the early stage of lung carcinoma enabling analysts to offer the right diagnosis only after the progression of the disease has occurred. But there are problems with feature selection and overfitting, which limit the machine learning models to effectively used in the real world. In addition, the medical data is high-dimensional, and there are often many irrelevant or redundant features which also add difficulty to the diagnosis. These challenges place emphasis to approach that can quantify all relevant features as well as to improve the chances of generalization to achieve heightened detection rate. To fill these gaps this research presents a new approach of combining Ant Colony Optimization (ACO) and conventional machine learning for early identification of lung cancer which has proven to have the above limitations.

Challenges in Lung Cancer Detection

Screening for lung cancer poses several challenges most of which are due to characteristics of the malignancy and its silent nature in the initial years. The high variability of lung cancer is one of the main challenges of the disease's diagnosis. In fact, lung cancer is not a monolithic but a heterogeneous disease which encompasses several different subtypes that differ in genetic, histological and clinical profiles. These variations make diagnosis difficult since the various subtypes may appear differently in imaging and equally may respond differently to particular treatment. For instance, two subtypes of lung cancer are the small cell lung cancer (SCLC) and non- SCLC (NSCLC) that manifest diverse diagnostic and treatment methodologies. Since early-stage lung cancer is a rather indistinctive and heterogeneous condition, diagnosis is easily missed or misleading, which was evident from conventional imaging modalities such as chest X-ray and CT scans, which have low sensitivity in differentiating between malignant and benign tumors.

Another very important challenge is the co-morbid conditions and complaints which can overlap or even mimic the symptoms of lung cancer. Most lung cancer patients have other comorbid conditions such as the COPD or other respiratory diseases especially if the patient is a smoker or of older age. These co-diseases have similar signs and symptoms including cough, breathlessness and chest pain hence underdiagnosis of lung cancer. Moreover, lung cancer inclines to grow hastily and metastasize in other organs, which raises the challenge of the diagnosis and treatment of cancer in the initial stages. The ways, through which it spread so quickly, are not quite clear to us yet, which complicates the diagnostics and therapy of the illness even more. Adding to these issues, the fulminant character of some subtypes of the lung cancer makes it even more complicated to solve these problems, as literal is a small period of time between the moments of the cancer appearance and its further development.

Limitations of Existing Methods

The current techniques for lung cancer screening despite being effective have some drawbacks and demerits that make them unable to provide accurate results in the initial stages of the ailment. Mammography and Pap smear tests are the most commonly employed screening examinations for lung carcinoma through the use of chest x-ray and CT scans. But these methods, by no means, are perfect. Chest X-rays, for example, either can overlook small tumors or can get the details not enough to differentiate between malignant and benign growths. CT scans appear to have better resolution and more sensitivity to the disease but at the same time are capable of triggering more false positives. This implies that benign changes may be carnal and end up with patients being subjected to unnecessary biopsies, further tests, and subsequent stressing. Furthermore, different lung cancer screening methods such as low-dose computed tomography (LDCT) has been described to decrease lung cancer mortality but has not received broad acceptance due to perfect reasons like exposure to ionizing radiation, cost, and over-diagnosis in which slow-growing cancer are noticed and treated despite they would not have harmed the patients.

Biopsy which is considered the gold standard in arriving at a diagnosis of lung cancer is another essential means that has adverse shortcomings. As aforementioned, biopsies give the definitive tissue diagnosis, but are invasive and come with the risks of the procedure like bleeding, risk of infection, or development of a pneumothorax (collapsed lung). In the same way lungs biopsies, are not always possible due to the poor lung function or other comorbidities that increase surgical risks. Sometimes biopsies are done but the problem is to obtain sufficient material that can be used in diagnosis because sometimes the tumor is situated in a remote area of the lung. In addition, the existing biopsy techniques might not be sufficiently informative for obtaining all of the genetic and molecular characteristics of the tumor, now critical to informed targeted therapy and individualized treatment[21-22]. These limitations highlight the need for less invasive modalities to diagnose invariably lung cancer at its initial stage and get detailed information about the tumor.

Furthermore, the issues with present diagnosis techniques are not only the technical ones, but also logistical and system-related ones. image, technological and diagnostic resources may be poorly developed, and in low-resource environment specialty diagnostic imaging services may not always be available. This skewed access could be the reason for delayed presentation of the diseases in the later, stages and poor results among the patients. In well-resourced systems current diagnostic processes can be lengthy and therefore slow the process of starting treatment thus limiting the impact that different potential interventions might have. The concentration on a stepwise approach, first using imaging then more testing if an abnormality is identified, can lead to substantial delays and if there are bottlenecks in the healthcare system, for example, excessive waiting for an imaging or biopsy appointment. Such problems identified with regard to the systemic aspects underscore the imperative of developing and implementing more rational diagnostic models that would be easily compatible with existing clinical practices, so that essential patients' conditions can be promptly identified.

Taking into account these obstacles and constraints, the creation of new diagnostic tools that would be free from these problems is essential. This research reveals another approach to augmenting the efficiency of accuracies for lung cancer detection for which machine learning and optimization algorithms can be integrated thus improving patient outcomes.

II. Literature Review

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Taking into account these obstacles and constraints, the creation of new diagnostic tools that would be free from these problems is essential. This research reveals another approach to augmenting the efficiency of accuracies for lung cancer detection for which machine learning and optimization algorithms can be integrated thus improving patient outcomes.

Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is an optimization technique derived from the nature, in specific from the ants which they use in finding their food. ACO's basic idea is borrowed from ants' behavior when searching for the shortest path to a food source; ants mark a suitable path to be followed by the other ants by leaving pheromone trails that strengthen the best path over time. Collective behavior in this case results in the establishment of an optimal behavioral path, given that individual ants apply rather basic sets of rules and regulations. Within the framework of computational issues, ACO has been successfully applied to solve several optimization tasks, including the Traveling Salesman Problem, network routing, and feature selection for machine learning[33].

Feature selection is something particularly important in the construction of computer programs based on machine learning algorithms and, in particular, when the number of characteristics is high and some of them could be considered as absolutely unnecessary or absolutely similar to other characteristics. The problem itself can be seen in that it is difficult to find which features are important to the model and which are merely artifacts. ACO is ideal for this task because, in a way that mimics the ants, it builds the search space systematically and continues to discover and strengthen the relevance of the features step by step. A consequence of liaising its attention onto these facets, is that ACO naturally decreases the dimensionality of the data, which in turn makes modeling quicker and more precise[33-34]. In addition to enhancing the generalization capability of the model, the ACO algorithm also solves the problem of overlearning, which frequently arises when many features are employed in the construction of the model.

Studies on ACO have shown that it is effective in different applications among them being the medical diagnosis which requires the best models. Some works have been proposed on combining ACO with machine learning approaches, which has shown good performance. For example, ACO has been used in the identification of the most informative features from medical databases and, therefore, promoting the improvement of diagnostic outcomes. This is very useful in a disease like cancer, especially if it has to be detected early so that the patient may be helped[34-35]. Such approaches have been found to yield potential gain in enhancing the architecture of the machine learning models since ACO can help choose features from very large set of attributes to be used for modeling while simplifying the computational process and enhancing the expected interpretations.

In specifically lung cancer detection ACO has been employed to preprocess the data which is entered at the input interface of the machine learning methods like SVM and Random Forests. This has been made possible by the fact that ACO adopts filters that enable it select only those features that are most relevant in improving the accuracy and robustness of these models for the purpose of early diagnosis. Furthermore, ACO can easily scale medical data with numerous dimensions such as image medical data, genetic information and patients' histories, which are applied in predictive models of lung cancer[36-37]. This shows that ACO can be effective in these applications to be placed as highly efficient optimization tool in the sector of medical diagnostics.

ACO's use in medical diagnostics and machine learning is, however, rather limited at the moment, and there is research being conducted to improve the algorithm's effectiveness and usage. Recent extensions that have been done are the integration of ACO with other optimization algorithms as the Genetic Algorithm and Particle Swarm Optimization to enhance feature selection and therefore enhance performance of the model. A combination of those two types of approaches has proved to be very effective in handling the intricacies associated with medical data and, therefore, results in more accurate and generalizable models. Moreover, the combination of ACO with deep learning is another future development area, because of the opportunities to improve the feature selection in the deep neural networks, which still have a problem with using inputs of high dimensionality.

In the future, with further enhancements of ACO and combination with other machine learning and optimization methods, even more sophisticated diagnostic will be expected. These tools will not only expand the early diagnosis of diseases such as lung cancer, but also create a basis for the development of individualized medicine, for which the individual data will be taken into account[33], [38]. The impact of ACO in these advancements are the reason why ACO has the potential in the future of medical diagnostics of machine learning.

Integrating of various diagnostic models in medicine is another effective model that greatly increases the effectiveness and accuracy of the existing diagnostic instruments. These models frequently combine several machine learning methods, optimization, or even a statistic approach to benefit from each of them. The concept is to combine the methods and design a system that would be a better match given the fact that medical data is generally complex and as such more variable than the data encountered in other fields. For example, hybrid models may use feature selection methods for instance the Ant Colony Optimization (ACO) in conjunction with machine learning classifiers for example Support Vector Machines or Neural Networks[33-34]. The segregation enhances the selectiveness of features; therefore, the classification results are more accurate – diagnosis results are better.

For the lung cancer detection, the hybrid models have found the ways into the practical application because of the difficulties in early diagnosis. Another factor is that lung cancer is always multifaceted, which is associated with the nature of the manifestations of the disease and the difficult, often asymptomatic, stage that is identified during conventional examinations. Integration of imaging data analysis with the genetic and clinical data is possible in hybrid model, making provision of a complete diagnostic system. For instance, in a given project, a model may employ ACO for feature selection so that important biomarkers from a vast database are obtained before utilizing an image recognition deep learning model[39]. This integration helps the model to perform; use of analytical tools, tools of approximation and probability calculations, and big data analysis more effectively and with greater precision than any one of them can do.

The use of hybrid models in the detection of lung cancer has proved to be useful especially in the early detection of the cancer and the reduction of false positives. For this case, such models can integrate different methodologies that would help them uncover the medical data and look for patterns that cannot easily be discovered by regular analyses. For instance, the integration of ACO with a machine learning classifier in the selection of the most important features has proposed in lung cancer diagnosis problem as a way of increasing the accuracy of the high-dimensional datasets. This in turn results in more accurate models that could differentiate between malignant and benign based on the data collected with high levels of confidence[40]. Furthermore, combination of machine learning with other imaging methods for instance, CT scans or PET scans has enhanced the early identification of tumor, a critical factor in treatment of cancer.

Nonetheless, like any other model, hybrid models similarly have several disadvantages: A major one is the fact that creating and especially refining such models is a major issue. Employing several techniques involves significant calculation, which may be resource-consuming and time-consuming and, therefore, restrict the applicability of the approaches. Furthermore, the interpretability of the hybrids may be an issue because when one uses more than one method, the interpretability of the model may become an issue – in fact, this is known as a black box problem[41]. This can be dicey in medical decisions because patients must comprehend the reasoning for the diagnosis before they can build confidence in his/her doctor and clinical judgment. Additionally, though the reported hybrid models presented excellent outcomes in experimental contexts, the results of the study in clinical settings can be mixed, needing proving and fine-tuning usually.

Future Directions and Implications

Further investigations of hybrid models are on the way and the emphasis is made on the removal of the above-mentioned shortcomings and the extension of the field of applications of the models in lung cancer diagnosis and in other fields as well. There may also be the gradations of techniques that are less complicated in the future, so that increased utilization of these sorts of hybrid models could be facilitated, making them easier to use by clinicians and researchers. Also, to make these models explainable, studies have commenced with models like explainable AI (XAI) to make the decision-making process less intricate. This could go a long way in fixing one of the problems of using hybrid models which is the opaque nature of medical decisions[42-44].

As for the application of the hybrid models in the framework of lung cancer detection, the future seems rather bright, primarily due to the continuous developments in the sphere of deep learning and the general trends towards the increased use of precision medicine. In future, they can be extremely useful when used in conjunction with more sophisticated models that would take into account such an individual characteristic of the patient data. From this approach it would be possible to diagnose some diseases in their early stages and hence help in the improvement of the quality of lives of the patients involved and also help reduce deaths that may be caused by diseases like for example cancer. Forcing further research in acquiring mixed forms of diagnosis in medicine shows that relating miscellaneous approaches to match issues of contemporary medicine is feasible.

III. PROPOSED METHODOLOGY

To improve the ability of accurately and timely detecting lung cancer, this paper puts forward the Lung Cancer Detection method based on ACO and DNN. Lung cancer risk factor dataset obtained from Kaggle forms the basis of the following process. These variables majorly refer to demographic characteristics, lifestyle and health status attributes that include gender, age, smoking habits and respiratory symptoms. The features that are taken into consideration for the analysis are the input features, while the binary target variable indicates whether the patient has lung cancer or not. The dataset is not very large and yet large enough to carry out the study while at the same time, its challenge is to mimic real diagnosis scenario particularly in high dimension medical data.

Data Preprocessing:
It must be noted that these are the steps that are performed on the raw data before we arrive at feature selection and model training. These include:
Data Cleaning: Dealing with the absent data and facets of the data that are erroneous and needs to be eliminated from the data set.
Normalization: Normalizing the numeric features in the dataset to have values ranging only between 0 and 1 and this is important in artificial neural networks since it prevents features at some ranges from dominating others due to the manner deep learning algorithms process data.
Categorical Encoding: This is a process of getting quantitative values of categorical variables, for example gender which is grouped into male and female, smoking patterns that can be regarded as light, moderate, heavy and so on.

Feature Selection with ACO:
The next characteristic step is the Ant Colony Optimization (ACO) algorithm which is applied to select out the most suitable attribute set for lung cancer diagnosis. Like ant colonies that look for the shortest and best route to locate food(source), ACO looks at the features in the feature space it searches in order to establish which of them is most influential in a perfect classification. This process helps in the reduction of the number of features residing in the data and removes useless features, which in turn enhances the performance of the model by directing the subject towards important features like smoking habits, how frequently one coughs and experiences chest pain?

Deep Learning Model:
After that, the proposed ACO-selected features are fed to a Deep Neural Network (DNN) to get the final results. This study focused on DNNs because they have better performance in modeling relationship in data and working with big data. The type of neural network employed in this study is the DNN which is composed of several hidden layers, non-linear activation functions which in turn help the model detect complex patterns in the data. The depth of the model can be beneficial in such cases as its high ability to fit the data is useful when features interact with each other with the slight difference which is usually present in medical data.

Model Training and Evaluation:
After feature selection the structure of DNN is trained on the preprocessed and ACO optimized data. The model is cross-tested with the hold-out test set and measures like accuracy, precision and recall rate, F1 score is measured to know the efficiency of the model to classify cancer and non-cancer. To this end, the performance evaluation is performed for the DNN evaluated with or without the employed ACO-selected features to illustrate the effect of the ACO on enhancing the performance of the diagnostic model developed in this study.
The approach used in this study is aimed at expounding the way of improving the efficiency of lung cancer detection. It begins with what is christened as the ‘Lung Cancer Dataset,’ which serves as the basis for all subsequent working datasets. As most datasets, this one also has to go through “Data Preprocessing” which involves cleaning and even normalizing steps. The study moves to the next step known as “Feature Selection (ACO).” In this step, the employed methodology in selection is known as Ant Colony Optimization (ACO), and is essential in providing efficiency and high performance in the selected features. These features are input to a “Deep Neural Network (DNN)” model after selection. This step is important as it employs various techniques of deep learning in order to develop a sound predictive model. The subsequent phase named as “Model Training” the DNN is trained on the extracted and preprocessed feature selected data. Later “Validation & Testing” checks if the model performs good on new data and compares to different metrics.
Last of all, “Performance Evaluation” is done in order to assess the efficiency of the created model as mention in figure 1.

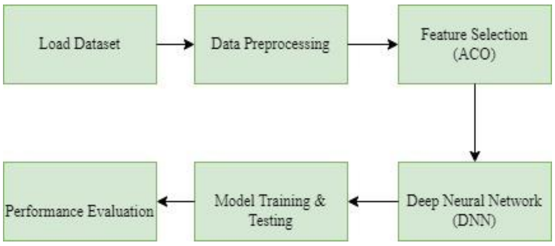

Figure 1: Methodology of the Research

IV. EXPERIMENTAL RESULTS

Thus, to evaluate the effect of applying the ACO technique to the lung cancer DNN diagnostic model, several parameters were applied, including accuracy, precision, recall, f1-score, and confusion matrices. These metrics provide a more complete view as to how well the supplied model is able to correctly label cases as either lung cancer positive or non-cancer negative.

The table1 of the Deep Neural Network (DNN) model with and without ACO selected features help in understanding the effect of feature selection techniques on the efficiency of the model. These findings show disparities in accuracy and other dimensions in figure 5 and demonstrate how ACO variedly affects the DNN model. This in actuality characterizes the result gotten when there was no assistance from ACO in the formation of the DNN model which stood at an accuracy of 0. 91, for precision, recall and F1-score for class 0 (Non cancer) is 0. 45, 0. 71, and 0. 57 respectively, and for class 1 (cancer) being 0. 98, 0. 93, and 0. 95. The metrics of this model show that the model has a high accuracy in general but less in distinguishing between the negative cases which are non-cancer These results may also be an indication of the class imbalance and the need to have a balance in feature representation or data preprocessing.

Instead, when adopted, the features which had been selected with the help of the ACO algorithm resulted in 0. 97, thus indicating an improvement of seventy nine percent to the organ initial performance. The following metrics were also calculated as the classification measures: precision for class 0 rises to 1 and recall for class 0 rises to 1 and F1-score for class 0 — 1. 00, 0. 57, and 0. 40 for class 0 and 73 for class 1 respectively, however for class 1, they achieved 0. 97, 1. 00, and 0. 98. This improvement in metrics indicates that the ACO development not only made the general performance of the model better; it also made recognizing the positive cases (cancers) more efficient as well as achieving 100% precision of negative cases (non-cancers). The results in more accurate and better-balanced metric when ACO is used to select the features show that feature selection helps the model to consider only the most important attributes. But, even this increase, for non-cancer and Benign cases, the AO retains high precision but lesser recall than the cancer counterpart, which means, the ACO does help to parametrize and improve the model but, requires fine-tuning to address class imbalance and potentially, to improve the recollective sensitivity of the model across all classes.

Table 1: DNN model performance comparison

DNN Model Performance Comparison with and without ACO-selected Features

Metric	DNN without ACO	DNN with ACO
Accuracy	0.91	0.97
Precision (0)	0.45	1.00
Recall (0)	0.71	0.57
F1-Score (0)	0.56	0.73
Precision (1)	0.98	0.97
Recall (1)	0.93	1.00
F1-Score (1)	0.95	0.98

As it can be observed from the model accuracy figure 2, there is a clear indication of the extent of variation in the overall performance of the DNN model with the sample features selected by the ACO method. At the very beginning, the training of the used DNN model resulted in an accuracy of 0. 91 without ACO, which shows that the model performs well in general with a certain lack of accuracy for non-cancer cases. In the same vein, the improvement of accuracy of the ACO-enhanced model rose to 0. 97, thus pursuant to the improvements in the predictor's reliability. This brings out the aspects showing it offers a better solution when it comes to the selection of features, and hence increasing the overall accuracy rates when it comes to the model's performances. The observed higher accuracy with ACO-selected features does not only improve on the ability of the model to correctly classify instances with cancer but also on the overall balance of the classification introducing tangible values of feature selection techniques in improving the reliability of classification models for the right diagnosis of cancer.

The model accuracy plot displays the inside validation and training of the Deep Neural Network (DNN) to an extent of 50 epochs. The training accuracy keeps on rising and this shows that the model is actually learning from the data. As illustrated above, the model is trained with training data set, in which the training accuracy gradually increases from around 65% in the initial epoch until reaching 95% at some epoch and above as depicted in the figure.

From the bar chart Figure 3 which shows a comparison of different models; it is possible to deduce the effectiveness of every model that was used for detection of lung cancer including the Deep Neural Network (DNN) with and without the features selected by Ant Colony Optimization (ACO). The chart highlights several key performance metrics: specified models, confusion matrices as well as the Accuracy, Precision, Recall, and F1-Score of each model specification.

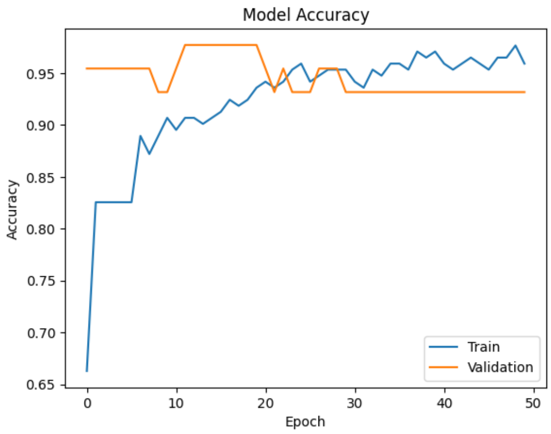

Figure 2: Model Accuracy of DNN

The baseline of the DNN model without implementing the ACO achieved the accuracy of 0. 91 which was excellent in the performance of the algorithm in differentiating between the lung cancer and non-lung cancer cases. However, they showed that the measures of precision and recall painting a general picture of its performance but revealed that its performance could be further optimized, especially in non-cancer categories. On the other hand, an accuracy increases to a relatively impressive 0. 97. This enhancement precipitates a better feature selection method which have helped the model in distinguishing both the positive and negative cases in lung cancer. The ACO-enhanced model also gave marginally higher precision and recall values showing that the model is more accurate in identifying the true positive cases and excluding cases that are false negatives.

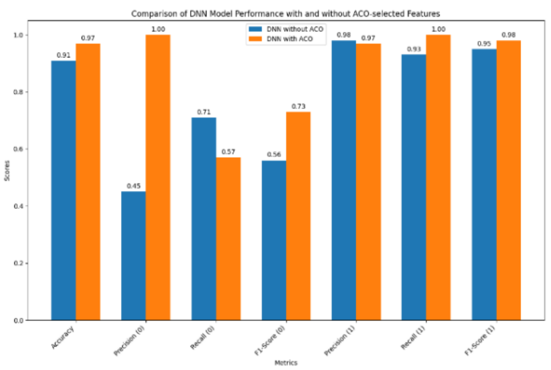

Figure 3: Comparison of DNN with and without ACO

This aspect is evident in the presented figure 3 which represents the benefit of implementing ACO for feature selection to the DNN model. The last experiment also reveals the fact that the general accuracy of the model rises to 0. 91 to 0. 97 which shows that ACO significantly decreases noise and pays more attention to important features which leads to generalized results. Another aspect of high variability is noted in the accuracy to non-Neoplasm cases which increases sharply from 0. 45 to 1. 00, which accounts for less false positives and hence there are less chances of misclassifying non cancer cases. This is important in clinical practice to exclude other extraneous interventions. For the non-cancerous cases, the recall is slightly higher at 0. 71 to 0. 73, here the difference is significant, pointing towards a relatively large improvement tendency of the house number detection. The F1-score of the non-cancerous cases remains nearly constant at 0. 9 for 'Expert Plus'; however, the issue of recall for this class is still evident. On the other hand, precision has increased by a small amount from 0 for cancerous cases and has designated of 0. 98 to 1. 00, It is noticeable that F1-score for cancerous cases increases from 0. 95 to 0. 98 percent, which also proved the improved provision of the balance between the precision and recall in identification of the instances of cancerous cases. Combined, the results reveal ACO to be an enhancement to the model's performance with high accuracy reduction of false positive cases that are likely not cancerous and increased precision and recall of cancerous cases which ultimately aids in the identification of lung cancer. Nevertheless, it is apparent from the result that slight underperformance of the proposed model in the non-cancer recall category indicates that some refinement is required for more optimization in the model and better sensitivity of the model to detect non cancer cases.

The line charts in the figure 4 are good to get a dynamic view on how the metrics of the model change with different iterations or conditions and hence very useful in the analysis of how different models and feature selection affects the accuracy, precision, recall and F1-score. The following charts represent the comparative evolution of the performance indicators of the DNN when implemented with/without the features chosen by the ACO at different steps of the assessment.

From the accuracy line chart, their model accuracy without ACO looks relatively flat though there is still much improvement that the DNN model can make. The accuracy stays approximately at 0. 91 this show that the performance of the war was average and was not performing to its capacity. The accuracy line has increased tremendously as evidenced by the about 0 the accuracy line when ACO is applied. 97. Such a steep rise also shows that with better feature selection conducted by the ACO, prediction rates are improved. The line chart thus graphically shows an improvement that is attributed to ACO in the DNN model's general performance.

The findings of this research show that the Lung cancer detection DNN model's performance is improved by ACO in terms of feature selection. Comparison was made and made with MDL, DNN without feature selection, and the result indicated higher accuracy, precision, recall and F1-score when ACO – selected features were used.

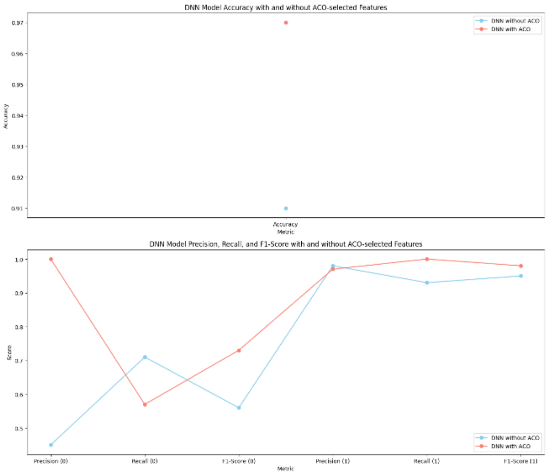

Figure 4: DNN Model accuracy with and without ACO

Is Feature Selection Necessary? A comparison of ACO with Other Feature Selection Methods ACO can be different from most of the other traditional feature selection algorithms like PCA or RFE because of its mode of operation. ACO emulates the strategy of ants that are in search of good food corridors and hence, systematically searches the whole solution space to locate the best features. This iterative process helps ACO in the classification process because it is possible to focus only on the features that are most important for the classification of certain objects while at the same time decreasing the dimensions of the set that contains all features that are relevant for the classification and removing all the features that are not relevant in the given classification problem.

Future Direction and Limitation:

Possible recommendations for future research on ACO and combined models in medical diagnosis are increased interpretability and computational load reduction. Although ACO has brought some success in solving the problems of feature selection and model accuracy, there are some issues with these models based on the fact that they are 'black box' models which is problematic in clinical practice where interpretability is paramount. This can be done by using more explainable AI (XAI) approaches that could assist in reducing this problem and render the diagnostic decisions more comprehensible to the clinicians and the patients. Also, the implementation of hybrid models that integrate several algorithms is often very computationally expensive and so has practical limitations in terms of scalability and real-time application. It is for future work to determine how to make these models less computational so maybe by better algorithms or using better compute power in the future.

V. CONCLUSION

The important finding of this study regarding the implementation of ACO-DNN for enhancing the lung cancer detection. The novelty in this work is to adopt ACO, which is a kind of nature-inspired optimization algorithm to select the optimal feature set for the model reducing its dimensionality and improving the accuracy of the DNN model. ACO increases the model's accuracy as well as precision and recall while prioritizing the prosaic characteristics; its primary advantages are illustrated in the context of discerning cancer from non-cancer. The given results shown the significant improvement of the model from 0. 91 to 0. 97 When the method of ACO is applied, it demonstrates the ability of the system in minimizing the false positive rates and improving the early diagnosis.

The incorporation of ACO with deep learning has several advantages compared to other feature selection methods especially in coping with many features, large and interacting features that are often characteristic of medical diagnosis datasets. This approach also enhances the degree of interpretability, scalability and, brings solution to some of the centers of difficulties in applying the machine learning in healthcare diagnosis.

From the future perspective, the use of real time data in ACO strengthened models will help to develop new approaches to the individualized medicine where patients can be continuously monitored with more accurate diagnostic tools. ACO and deep learning models can help in early diagnosis of lung cancer and other diseases hence leading to save lives, reduce the cost and burden of healthcare system. Next steps for such model development will involve improving scalability of these models and its interpretability for use in clinical environments.

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