Advances in Hybrid Models for Early Cancer Detection: A Systematic Review

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Abstract: *Cancer is still one of the greatest ailments to affect human health, having far-reaching influences from physical to emotional, social, and economic. Despite treatment, early and accurate detection is still the most critical strategy for maximizing survival rates. In the past few years, hybrid computational models integrating machine learning (ML) and deep learning (DL) have been reported to perform better in cancer detection than traditional single-algorithm solutions. The current study provides a critical review of hybrid diagnostic models that utilize the advantages of standard ML classifiers, deep neural networks, and multimodal imaging strategies to achieve higher precision, explainability, and clinical adoptability. The survey encompasses the entire spectrum of hybrid systems from SVM–KNN, K-Means–GMM, Boruta–SVM, CNN–GRU/LSTM, CNN–ELM, to meta-learning–ANN hybrids to advanced multi-step ensemble systems involving models like YOLOv5, MedSAM, DCGAN, and edRVFL. The frameworks integrate complementary capabilities—feature extraction, segmentation, augmentation, and classification—to deliver end-to-end cancer diagnoses. Empirical assessments in various studies show diagnostic accuracies of 95–99.9% on breast, cervical, and lung cancer datasets such as WDBC, MIAS, and CBIS-DDSM. Besides, transfer learning-hybrid approaches with pre-trained models such as ResNet, EfficientNet, and VGG have successfully resolved data insufficiency problems, while ensemble learning enhanced generalization and reduced overfitting. The paper also presents sensor- and imaging-based hybrid systems in which multimodal imaging information from PET, NIR fluorescence, and intraoperative ultrasound is combined with AI-driven analysis for improving tumor localization and real-time clinical decision-making. IoT-supporting intelligent sensors, edge computing, and federated learning topologies enable new paradigms of privacy-safeguarding, decentralized cancer diagnosis that can operate in real-time as well as resource-limited environments. Despite these advancements, the research highlights specific challenges like significant computational cost, model interpretability, class imbalance, and unsatisfactory cross-domain generalization. The research concludes that hybrid ML–DL and multimodal models are a paradigm shift in oncologic diagnostics—they transform traditional workflows into smarter, dynamic, and scalable AI-based environments for facilitating early, accurate, and personalized cancer detection and prognosis.*

Keywords: ***Hybrid Machine Learning, Deep Learning, Cancer Detection, Medical Imaging, Ensemble Framework, Multimodal Diagnosis, Precision Oncology.***

1. Introduction

Cancer is commonly referred as one of the most inextricable diseases in the upcoming age which going to affect humanity in multiple ways like by means it physical problems, emotional, social or economic. We know Cancer is not a single cause of death in Human in which cell grows uncontrollable and spread throughout the full body of those abnormal cells. Development and advancement in medical field have increased survival rate of patient from death from cancer in the past few decades, but still, it is one of the exponential leading causes of death worldwide.

The most immediate and direct impact of cancer is experienced by those people who are diagnosed with it. Patients suffer from many physical challenges including pain, fatigue, nausea and more serious consequences such as weakened immunity. There are many cancer treatments through which we can cure cancer such as chemotherapy, radiation therapy they can be lifesaving, but still, they are often harsh and place a heavy burden on patients.[1] [2]

On the emotional, cancer generates deep psychological strain. Patients often grapple with anxiety, fear of mortality, depression, and uncertainty about the future. The very word “cancer” can strike fear, as it is still associated in many cultures with incurability or inevitable death, despite medical progress. For children and young adults diagnosed with cancer, the disruption to their education, social interactions, and future aspirations adds another dimension of suffering. Cancer not only affects patient but also beyond this it's also affects the patient’s families and their caregivers and relatives. They endure burdens while supporting their loved ones. Watching beloved one suffering from cancer is traumatic, and caregivers often face stress, sleeplessness, and exhaustion to their caregivers and families. The dynamics of family life shift significantly, with roles and responsibilities changing abruptly.

We know treatments and cure of cancer diseases makes financial pressure and burden on patient and patient’ families, especially in countries with limited insurance coverage or weak healthcare systems. The main financial burden come from cost of treatments like consultations, diagnostic tests, medicines, hospitalizations, and post-treatment care. Many households have to take loan to treat the cure of cancer of patient and fall into loan dept or sometimes poverty. So thus, cancer not only affects patient’s body but also affects patient’s family by disbalance their emotional state and destabilize family structure and their lives. Apart from patient and their family’s cancer also affects society and the stigma surrounding cancer also influences how societies respond to it like in many communities, patients suffer not only from the disease but also from social isolation and discrimination[3] [4].

On the other hand, cancer has also brought humanity together in different powerful ways such as Awareness campaigns, fundraising drives have founded solidarity and compassion. Many social workers arrange this type of campaigns where they aware society from the consequences of cancer and motivate drinkers and smokers to change their habits. Survivors often become advocates, inspiring other people with their resilience and contributing to breaking the stigma.

Despite its devastating impact of cancer, it has also been a catalyst for innovation like different method and model to detect cancer cell in its early stage efficiently and scientific research to understand different nature of cancer and cure and treat it. Research into cancer biology has led to groundbreaking discoveries, such as understanding genetic mutations, developing precision medicine, and harnessing the immune system to fight tumours. These advances not only improve cancer treatment but also make it less expensive so that poor people also able take benefits from that. Cancer is not only a medical condition it is more than that, it is found as challenge that affects individuals, families, societies, and nations. It drains resources, shatters many lives, and tests their endurance, yet it also inspires advancements in research, innovation and medicine to cure cancer diseases safely and efficiently, it also nurtures compassion among people and strengthens the resolve to protect human health. Although the process to conquering cancer is take time and road to completely able to cure cancer is long ahead of us, but the effort of humanity to prevent detect and treat the cancer symbolize the hope that one day we will overcome on this. [5] [6]

1.1 why hybrid models?

In the field of medical science where diagnostics for complex diseases like breast cancer, lungs cancer etc., single algorithm cannot work best on every type of cancer detection for everyone. Different type of detection models has their own way of detection of cancer cell and so they have their own strength and weaknesses. Deep learning model is great in analysing complex visual data from images and new pattern, while traditional machine learning model excels at statistical classification but depends on pre-defined features.

Traditional way and single model of cancer detection have some limitation and to overcome these limitations and solve problem related to traditional and single model based, hybrid models are developed. These models combine the best aspects of different machine learning model into a strong hybrid unified system. For example, in CNN+ViT model CNN captures local details and ViT understands global context for highest accuracy and overcome Data overfitting. By combing different hybrid approach makes diagnostic tool more reliable and accurate which helps medical professionals like doctor so that they make better decisions and improves patient outcomes. [7] [8]

1.2 Strategic Advantages and Enhanced Performance

The principal advantage of the hybrid solution is the higher improvement in correctness and efficiency. In support of the claim, the studies in various researches have proved that the hybrid solution is invariably more superior in terms of performance compared with other models. In the study of the research analysis of the performance of the solution, the hybrid solution was denoted as “AZL” with the combination of three models of the deep convolutional neural network (D-CNN), which is amazingly remarkable with the accuracy of 99.92%. In the study of the other research analysis of the performance of the solution, the solution with the combination of meta-learning method and the Artificial Neural Network (ANN) models was of higher accuracy with the basic concept of 98.74%. Apparently, these studies vindicate that the hybrid solution with its respective algorithm or solution is invariably superior in presenting predictively correct results compared with the stand-alone solution. The correctness of the solution is not only long-term in relation to the higher accuracy percentages because the hybrid solution with the application of the deep learning algorithm possessed poor accuracy of 99.7%, in spite of the tremendous speed of its performance with 0.75 seconds that is broadly declared as absolute in the critical point of view in the hospitals. It is because of the reason that the hybrid solution invariably comprises of different superior models that work in cooperation with the aim of the better correctness and efficiency. The principal strategy of the hybrid solution in the higher correctness is the concept of functional specialization. In the concept of the functional specialization, the models work automatically without the professional need of the others with the independent performance of varied tasks in the separated manner in the specific concept of the diagnosis or decision-making. In this regard, the extremely superior pre-trained deep learning solution with the application of the algorithm has some abilities that work in the capacity of the automatic acquisition of recognition of the varied complex feature in the histopathological image. The feature is initially enhanced with the more superior correctness through the application of the extremely superior machine learning solution with the application of the algorithmic solution denoted as “LightGBM,” that is the different type of hybrid solution that acts in the capacity of mixture of assist and stand-alone solution performance in the presentation of the superior correctness of the judgment of predictively correct performance of the varied models.

Further, another crucially important method employed within the hybrid model for determining the levels of correctness is based on the usage of the corrective model employing ensemble techniques that remove errors within the levels of correctness of the diagnostics by employing the outputs of the models to obtain higher levels of correctness because the models always differ in producing the similar unpredictable outcomes within the diagnostics because the similar errors within the diagnostics are avoided within the combined outputs of the models because the models differ, namely "AZL," employing the outputs of the diagnostics models like "AlexNet," "ZfNet," and "LeNet," to obtain the final decision on the higher levels of the unpredictable outcomes because the models have failed within the diagnostics because the outputs differ because of the level of misclassification of the diagnostics.

One of the advantages of the hybrid deep learning model is that the system possesses a tremendous speed in terms of its processing, regardless of the number of computations involved in the model itself. [5][9][10]

1.3 Inherent Limitations and Practical Challenges

Despite such superior performance, there are some challenges associated with these models, which must be identified. The first and also foremost challenge related to enhanced complexity is the cost of computation associated with these models. This is due to the fact that training several models at one single instance is a way more cumbersome process in relation to the use of one single model or algorithm. In fact, this may likely prove to be a challenge as one of the research studies identified that for carrying out the hyperparameter optimization process, the sum of a million trials is to be completed in a span of a couple of days using a high-performance computing machine. Therefore, at the advent of this challenge related to greater computing needs, this challenge may continue to serve as an obstacle in using this specific model or algorithm within the real-time clinical practice environment or within the overall healthcare environment using a low-performance machine. Moreover, besides this particular challenge associated with greater overall complexity and resultant difficulties associated with overall associated computing needs, in order to perform with an overall/optimal degree of success in a hybrid mode, this particular challenge associated with overall model performance perchance relies upon the overall quality of these models individually as well as the overall quality of these models' respective training models which are in a position to provide an overall degree of input into the overall performance of these models individually as well as in a hybrid mode in a better manner in relation to other models or algorithms of the similar nature that are in use in relation to the sort of overall input associated with these models individually as well as in a hybrid mode in the overall healthcare environment or in a particular clinical practice environment which may have overall greater associated needs associated with overall associated needs in relation to associated higher associated levels of performance associated with these models in a better manner in relation to other models or algorithms of the similar nature which are in use in relation to associated overall similar needs in relation to associated greater overall needs of a similar nature associated with overall associated models of a similar nature which are in use in relation to generally overall associated needs in relation to overall greater levels of overall performance in relation to associated overall models of a similar nature which are in use in relation to generally overall similar needs in relation to associated models of a greater overall nature in the overall particular/clinical practice environment which may have overall greater overall needs associated with overall performance in relation to overall associated models of a similar nature in relation to generally overall models of a similar nature which are in use in relation to overall associated needs in relation to associated overall models of a similar nature which are in use in relation to generally associated models of a greater overall nature in an overall particular/clinical practice environment which may or may not have overall greater associated needs associated with overall performance in relation to associated models of a similar overall nature in relation to overall generally overall associated models of a similar nature which are in use at any point of generally overall associated times in relation to generally models of an overall greater nature in relation to overall models of a particular overall nature which have generally overall greater associated needs associated In these scenarios or situations, therefore, although these models or designs of algorithms may continue to be additionally advanced as regards the concerned domain or area of their expertise or relevance or usage, these may continue to be non-applicable or non-feasible due to certain higher costs or complexities of their related computations and data related fundamental or technical limitations, as already pointed out previously. [11]

1.4. Review of literature and relevant research

Based on research studies, the models that are multi-sensor and multi-modal imaging models prove to be very efficient methods for diagnostic uses. These models give a holistic opinion about cancer by combining information from different imaging modalities and have the benefit that these models are independent and do not depend upon a single imaging modality. For instance, these models can provide a combination of functional information from PET scans and high-resolution NIR fluorescence imaging and hence provide better visualization of metastasis. In reality, these models provide better surgical guidance, including intraoperative ultrasound and, in addition to that, intraoperative fluorescence imaging. [2][12] These models provide a possibility of making more accurate predictions with the use of machine learning to combine information from imaging and genomic data, respectively, and provide a holistic opinion about the relation between the development of a tumour and its molecular characteristics.

From the year 2015, deep learning, with the application of CNNs, was at full steam when it came to cancer detection research. Deep learning CNNs eliminated the complexities involved with feature extraction, needing it to be done by humans, as it is able to learn features on its own directly from raw input sources such as mammography, histopathological, or CT scans directly. Allowing them to reach an unprecedented level of accuracy, at times over 95 percent, when it came to breast, as well as lungs, cancer detection methods. The development of EfficientNet, along with ResNet-50 [13][14] neural networks, proved itself to be able to extract very subtle features in high-dimensional images, far beyond the capability of convention machine learning algorithms. For example, when applied to digital mammography images, as well as histopathological images, CNNs were able to reach the best performance level when distinguishing between benign tumours and malign tumours, thereby reducing false positives and assisting doctors with their diagnosis [8]. However, it was also observed to have had some serious pitfalls, like it needing large amounts of labelled training data, high computational complexities, as well as the tendency to overfit, even with relatively smaller, as well as imbalanced, samples [15][3].

In this regard, the scientists were tasked with addressing these challenges through the integration of methodologies from ML and DL [16]. The scientists employed a hybrid approach that incorporated the strengths of both approaches at the same time. In this case, the scientists used methodologies from ML for feature extraction and then employed DL models for classifications. In this way, a hybrid approach that incorporated Random Forest and CNN for breast cancer detection not only offered improved interpretability but was also able to maintain the discriminative ability offered by DL models. In the diagnosis of lung cancer, two-model approaches that incorporated the integration of CNN with YOLOv8 object detection were not only capable of diagnosis but were also able to localize the cancer for quick diagnosis and preparedness for cancer management [4]

Another milestone in the evolution of hybrid approaches was the integration of Generative Adversarial Networks (GANs) [17] to address the persistent issue of data scarcity. GANs were employed to generate synthetic medical images, thereby balancing datasets and improving the performance of deep learning models trained on limited data.

Various cancers have also leveraged the hybrid ML-DL approach successfully. In the case of breast cancer, CNNs integrated with feature extraction techniques and ensemble classifiers have been a great contributor towards improving the accuracy of mammographic/histopathological image analysis. The Cervical cancer identification techniques have also seen a complete facelift with the use of hybrid techniques, for instance, the AZL ensemble model created out of combinations of AlexNet, ZfNet, and LeNet models, with an accuracy of 99.92 %. Skin cancer identification techniques have seen phenomenal improvement with the use of CNNs in conjunction with GAN-based image data generation techniques and give an accuracy rate equivalent to that of a dermatologist. Even in prostate cancers/bone cancers, hybrid models comprising the use of k-means clustering algorithms, Gaussian mixture models, and CNN classifiers have contributed toward increasing the accuracy of diagnostic identification. [5] [18] [19]

Hybrid ML-DL models use a variety of techniques in their approach. Pre-processing techniques such as adaptive histogram [20], CLAHE, and noise filtering improve the image quality before processing. Hand-crafted features such as Haralick texture features, GLCM, HOG, and LBP features are being increasingly combined with deep features derived from CNNs or transformers for a more comprehensive representation of medical data. Transfer learning applications include fine-tuning pre-trained models ResNet-50 [9], DenseNet, and EfficientNet models on a smaller cancer dataset, which reduces training time and processing requirements immensely. Ensemble learning methods can then improve generalization by combining multiple learners, whereas sequential feature learners such as LSTM and GRU networks enable modelling of inter-slice correlations in imaging data

Despite these impressive advancements, several challenges remain. Data scarcity and imbalance are persistent obstacles, as most cancer datasets are small and collected under controlled conditions that do not show real-world diversity. Generalization remains a concern, with many models performing well on one dataset but poorly on another.

The amalgamation of machine learning processes and deep learning algorithms has provided a accuracy enhancement in cancer diagnosis like never before and at a pace hitherto unimaginable. From being manual to the most advanced and difficult hybrid models embedding CNNs, ensembleing methodologies, GANs, and federated learning algorithms, it has been a resounding success right from day one.[12] The accuracy rate has been crossed by the hybrid methods of ML and DL at a rate of over 99 percent in clinical trials conducted for breast cancer, lung cancer, cervical cancer, and skin cancer, hinting towards a imminent cancer diagnosis revolution.[21] The future of cancer diagnosis would be governed by the paradigms of multi-models based on AI embedding innovation and medical expertise. Early diagnosis of cancer would be made possible at the same cost with unfailing accuracy.[22]

The amalgamation of IoT and AI is enhancing the cancer diagnosis with the help of smart and distributed systems in a way to overcome the limitations of existing approaches being used until now. The technological advancements begin with the help of IoT sensors and wearable technology with superior imaging technology, which helps in continuous data acquisition. This entire data is processed using hybrid AI algorithm; in other words, these help in using the best from deep learning with CNN and YOLOv8 algorithm together in a way to automatically extract all relevant information regarding biomedicine images and cancer detection using machine learning algorithms for solid and interpretable class predictions. The major success of these proposed approaches lies in critical key steps in image processing: contrast enhancement using CLAHE and advanced techniques in innovative features assessment with a combination of hand-crafted features like GLCM and HOG features with deep features in a deeper and in-depth analysis in a single and improved manner. Further, latency avoidance using edge computation for instant decision-making and federated learning with features that help in overcoming challenges and issues related to patient data confidentiality and security helps in ensuring the effectiveness of this technology with a suitable performance in a practical and real-world setup and providing answers for major queries. In addition, overlooking few unsolved queries associated with major technical issues related to data security and adaptability with a generalized model's setup in multi-specific domains and areas, this helps in disclosing better and better accurate, feasible, and customized approaches related to detection and diagnosis of cancer. Further progressing with imaging approaches will be a synergy with genomic and clinical data with a holistic perspective of patient management.

The hybrid models that pertain to cancer research signify the shift in paradigm in the analysis of data from one mode to a multimode combination in which an amalgamation of a number of sources of data from the field of medicine is merged to create a predictive model that is better. The predictive nature of the model in that respect is in the sense that it is not possible to understand the complexity of the data source that is human in nature that contains data in a file of the patient's record, genome, or images that signify a complex process called cancer.

Initially, the traditional machine learning algorithms like SVM algorithms, decision trees, and artificial neural networks (ANN) were examined and implemented in the research work done in [23]. These algorithms have been primarily used for either genomics or imaging characteristics. But adding other variables like age or treatment experience may have caused improvements in these algorithms as well. Initially, the results in these algorithms revealed that these combinational algorithms have the potential to offer a 15-20% increase in accuracy in terms of genomics algorithms in comparison to the results provided by statistical analysis[24]. However, with the rise in the availability of datasets and computational power, there came a shift in the direction of combined learnings inspired by deep learning approaches. CNNs became an essential component in the analysis of MRI, CT scans, and histopathology images, while analysis related to understanding the temporal aspects of clinical data was conducted using RNNs and its advanced versions like LSTMs. Hybrid solutions worked in tandem to analyze imaging biomarkers simultaneously with molecular biomarkers in order to attain an integrated understanding of the disease process.

Recently, all the above approaches have been further incorporated into a model that includes transformers, the use of attention mechanisms, and graph neural networks [16]. These approaches are also very successful on complex high-dimensional cancer data. They do not only identify features but also draw connections between the modalities itself, for example, how the mutations of the genes correspond to what differences are observed in the scans and the patient outcomes. Other techniques that are used here include multiple instance learning, transfer learning, and ensembles that would result in a stable model and prevent overfitting. This would greatly allow the use of these approaches within the healthcare domain.

In summary, the progression of hybrid cancer models reflects a clear evolution: from basic combinations of classical algorithms with small datasets to advanced multimodal systems that unify genomics, imaging, and clinical records. Such integrative methods are increasingly recognized as crucial for precision oncology, supporting not just early diagnosis but also patient-specific treatment planning tailored to individual biological and clinical characteristics.

2. Related Works

Datasets acquired clinically should be pre-processed i.e. filling in missing values and removing noise and image resizing. This process is done because the methodologies related to hybrid cancer detection model have a common backbone of intense data preparation and preprocessing. This step also includes image normalization, rotation, flipping, or other adjustments to generalize the image. This process is followed by filtering noise and dividing of data into different test sets. This process is often performed using k-fold cross validation to ensure robustness

First statistical and morphological features are taken and classified using an SVM to get the maximum-margin decision boundaries, then after KNN refinement for borderline cases, in the 2018 approach. Similarly in 2022, Baruta + SVM/others approach Baruta was applied for feature selection before feeding selected predictors into classifier models like SVM with an RBF kernel, helping reduce overfitting. In 2021 the K-Means + GMM hybrids were used, where K-Means provided coarse clustering initialization and GMM refined probabilistic boundaries via expectation-maximization. Together, these approaches show the power of combining global boundary learners, feature selectors, and local probabilistic refinements for improved diagnostic accuracy. [25]

Historically, conventional machine learning techniques such as SVM, KNN, K-Means, and GMM have been conventional in medical diagnosis based on interpretability, computability, and suitability for smaller structured datasets as opposed to deep learning, which requires big data. However, when employed separately, there may be some inadequacies considering the vulnerabilities of SVM to noisy features, KNN to irregular features, and possibility of convergence to a local optimum in clustering algorithms such as K-Means. These issues can be addressed by hybridization.

For example, in the 2018 SVM + KNN system, SVM was used because of its efficiency in determining the maximum margin hyperplane, which distinguishes the malignant class from the benign one, regardless of the number of features employed being high dimensional in nature. However, the strategy may fail when making decisions about where to classify instances which fall in the overlapping portion of the hyperplane, especially when morphologies of tumours in a particular case are in question. In such instances, an approach which relies on neighbourhood similarity, such as KNN, may be employed in conjunction with SVM in order to alleviate such difficulties. [26]

Similarly, the importance of feature selection in the context of cancer detection is also highlighted by Boruta + SVM (2022). In typical medical datasets, there are redundant or unnecessary features (such as useless image features). However, a feature selector using the importance rank of a random forest algorithm in Boruta identified features of statistical necessity for removal, ensuring exclusively statistically significant features were retained for the model to learn solely from biologically important patterns in the data. The use of optimized input features into an SVM with an RBF kernel, which performs nonlinear transformations, prevented overfitting in favour of generalizing well among groups of patients. The hybrid model's origin is in this "separation of concerns." Boruta ensures robust feature dimensional reduction, with decision-making by the SVM.

Another benefit is the hybrid model of K-Means+GMM. K-Means is efficient to get quick partitions but assumes spherical clusters and hard boundaries, neither of which will model biological variation or tumor shapes in general. By contrast, GMM models clusters as probability distributions through soft assignments by expectation-maximization to encode uncertainty and overlap between cancerous and non-cancerous samples. In order to make it computationally efficient while being strong in probabilistic modeling, starting with K-Means (to avoid GMM's sensitivity against random starts) and refining them afterwards using GMM yielded a hybrid method balancing computational efficiency with strong probabilistic modeling[25]. In short, these traditional hybrid pipelines were designed to combine global learning with local correction strength of features with probabilistic representation of uncertainty all tasks that a single traditional algorithm was unable to handle alone. This exchange allowed researchers to improve diagnostic performance outside of the single-model context, especially considering populations in which deep learning was unfeasible.

SVM models lack in sensitivity to noise, accurate decision-making, and the selection of features unrelated to high-dimensional clinical datasets. The KNN analyzes precise cases that are divided with respect to local context, making the model equally important to other hybrid models, which can fail due to one faulty algorithm. The SVM-based cancer detection model has a higher chance of overfitting and more robustness, which was fixed by adding Boruta models to it. This hybrid model fixed a major issue of feature extraction. Similarly, K-Means + GMM hybrid models gives out simple decision for complex problems analyzing real life tumour patterns, hence increasing flexibility in appointing datasets so that it doesn't overlap.

Another set of work utilized transfer learning techniques using hybrid CNNs. The 2024 study based on different variants of Efficient Net utilized the strengths of pre-trained CNNs and Efficient Net for creating robust representations. Transfer learning techniques facilitated the utilization of large-scale knowledge in medical imaging while performing fine-tuning tasks for breast cancer datasets. There was a combination of different backbones either using a concatenation strategy or an attention layer, and dense classifiers with dropout for regularization. The hybrid technique greatly improved generalization capabilities compared to the utilization of individual CNNs. [3]

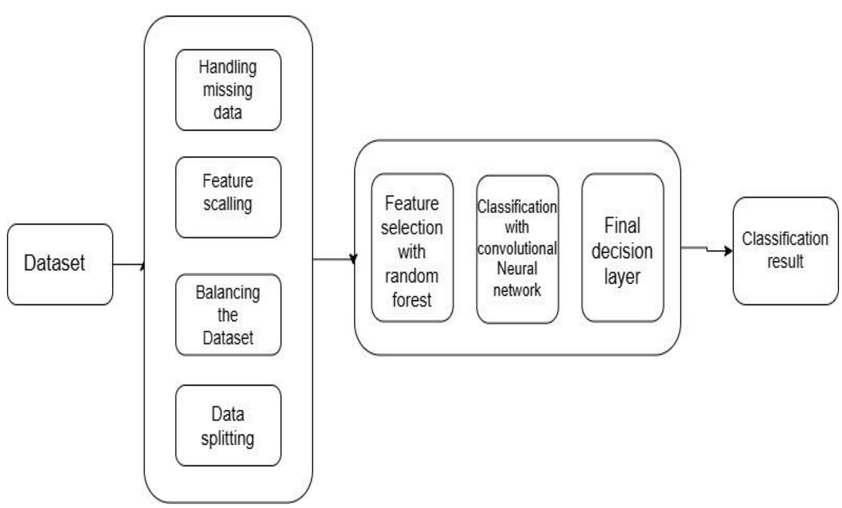

Fig 1: Architecture Diagram of Proposed Hybrid Model

Pre-trained CNN hybrids and transfer learning were made because of two challenges that exist in medical image-based cancer diagnosis: size and requiring partial features. In most cases, CNNs with or without fine-tuning have failed in medical imaging because of the lack of annotation, but in transfer learning, a network is able to capitalize on features learned through massive datasets like ImageNet. The abstraction at this level entails general visual features such as edges, textures, and shapes, which can later be used in fine-tuning for finding tumour-specific features.

For the EfficientNet-hybrid network in 2024, the features were blended by combining the embeddings of EfficientNet with other pre-trained CNN features like VGG or ResNet-50 [20]. The choice of EfficientNet was based on its compound scaling method, which is optimal in terms of depth, width, and resolution, making it very light and relatively strong in terms of feature extraction. However, this may potentially disregard very detailed characteristics of medical patterns. Hence, adding other CNN features with a perspective on the most dominant characteristics of patterns was done either by simple addition or attention mechanisms.

The classification stage also demonstrated the hybrid capabilities of the models. After the fusion of features, dense layers with dropout to combat overfitting and promote generalization were employed. In medical applications, dropout was a critical component, as it allows the neural network to learn redundant paths and does not rely heavily on a single set of features, which could be beneficial when there are imbalances in the datasets. By exploiting the robustness of transfer learning, the efficiency of EfficientNet [27], and the complementary strengths of different CNN architectures, the hybrids outperformed separate CNN architectures with respect to generalization and discrimination of the feature space.

This hybridization is important because previous CNN models were inclined to have problems like overfitting, restriction in feature diversity, and biasing towards a particular dataset. In this regard, using a combination of pre-trained models resulted in a diverse set of features and facilitated the identification of both local and global features in medical images.

The strength of the transfer learning hybrids lies in their ability to overcome the issue of the small annotated medical datasets. Traditional CNN models required large medical datasets related to the application domain for effective training. As a result, the models did not perform well on medical imaging due to poor generalization of models resulting from a lack of annotated medical samples. However, models present in the hybrid learning paradigm benefited from the pre-trained network representations such as EfficientNet [27], which provided excellent cues already optimized for millions of natural images. Moreover, feature fusions of multiple pre-trained models also picked up sensitive cues, not only about the high semantic levels of data but its textural details too. Furthermore, regarding the sensitivity of the former CNN models to the problems of overfitting and their poor transfer learning performance on these datasets, the hybrids provided significantly better performance.

The third set of models used the CNN + RNN hybrids to try and handle either volumetric or sequence image data. The CNN + GRU-based 2022 model processed medical images with the use of convolutional layers to learn spatial features that were then fed into the GRU layer for tapping temporal or slice-based features. A complementing lung cancer detection model from 2024 combined CNNs and LSTMs with the ability to tap sequence-based CT image data. Models of volumetric image processing, combining CNNs, which focused on spatial information in every image, with the use of RNNs, which detect sequence information in the images, proved very efficient since they combined the strong points of two different architectures.[28]

"CNN+RNN" is a cry for help in applying "CNN" and "RNN" only. "CNN" is most appropriate in feature extraction routines of images. "CNN" identifies images, textures, and tumours based upon comparison of images, textures, and tumours with a normal cell image, texture, and tumour. "RNN" synchronizes the hierarchy of models and helps in feature extraction based upon raw un-tagged data like images. Thus, a hybrid of "CNN" and "RNN," "CNN+RNN," complemented each other in coping with each other's weaknesses and making each other's strengths stronger.

At the beginning of 2022, CNNs were used for the detailed representation of the structure of tumours and were then passed on to GRUs for the use of retaining the ability to store information over a short to medium range and thus have been useful in medical applications with moderate ranges of information. In a similar fashion for the year 2024, a combination of CNN and LSTM has been used to create a hybrid technique that has the potential for memory retention in the long term. This was highly useful for the analysis of CT images that tend to have a huge number of sliced images through which the progress of cancerous growths could be easily mapped through a long sequence of images.[29]

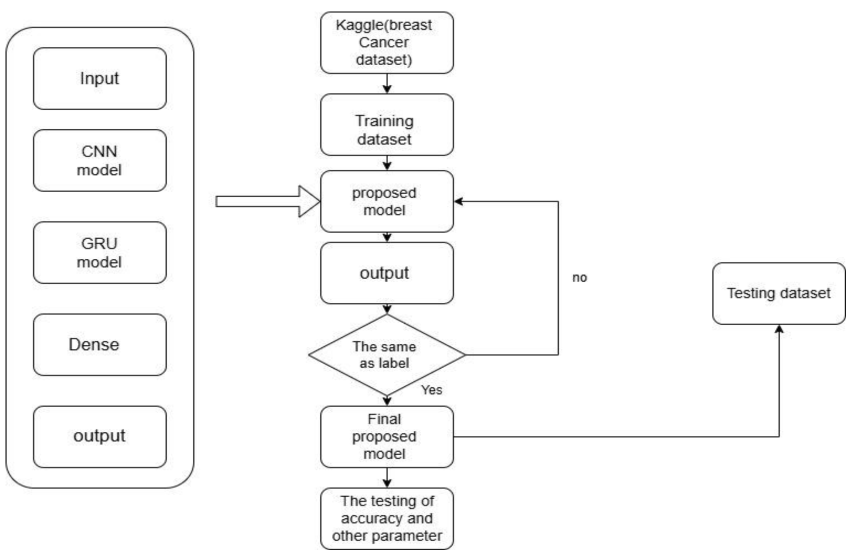

Fig 2: Flowchart of the Proposed CNN-GRU Model

The imaging features of CNN highlights tumour shape and its texture, whereas GRU and LSTM gather these over a period of time, hence creating a contextual and richer diagnostic signal. This shows the synchronization of RNN and CNN architecture. This proved that the models are capable to recognize the malignant area and understand how the area got affected in the first place.

Combining CNN and RNN provided a more thorough approach that accumulated the dynamic volumetric context and static spatial details of medical scans. This was important because CNN models only analysed a part of the image and usually missed some changes whereas RNN models cannot gather the detailed spatial features from the image. These changes highly improved the simple malignancy patterns proving their efficiency volumetric imagining techniques like CT scan, MRI etc.

In 3D imaging techniques like CT or MRI, one part of a image sometimes don't show malignant tumour features but simple variations among successive parts can show signs of malignant tumour. Rather than reviewing each image separately we can use GRU or LSTM models to show how the tumour is developing over a period of time. This resolves a major disadvantage in CNN models as they failed to keep a record of changes made to medical images over a period of time. CNN + RNN models also improves the chances of detecting minute malignancies in a tumour which were overlooked by CNN models. This helped in diagnosing cancer at an early stage as compared to other methods.

ANN models came as a technique which had a faster learning rate compared to other models as it used meta learning improving it's the speed of learning. This was highlighted in a 2022 study showing how hybrid models of ANN + Meta learning can help in early-stage cancer detection by changing the network structure as required. This gave a flexible approach in handling regular cases in hospitals, nursing homes etc. [11]

After going through various datasets, it is observed that it varies between hospitals, patient groups and various machines. ANNs usually performs well if trained with a single dataset from a single source and fails to do so if applied on another dataset. Thus, scientists combined it with meta learning to improve its learning rate and sometimes reorganizing based on a new dataset from a different source. This became a solution to the oldest challenge in the history of cancer detection, hence solving the problem of source-target mismatch of datasets.

The hybrid meta learning +ANN model dose not rely on a single network or dataset rather than it adapts itself to represent various network and datasets. This was made to make ANN more flexible, such as adaptable learning rate and using different techniques during training. For example, if the dataset contained highly imbalanced classes, the meta-learner could adapt the learning rate or adjust hidden layers to improve stability.

The ANN itself was built using regularisation techniques like batch normalisation and dropout. Dropout forced the network to learn duplicate routes to avoid becoming overly dependent on neurones, whereas batch normalisation-controlled training by normalising intermediate feature distributions. These methods greatly increased the ANN's robustness over static architectures by enabling it to function consistently across a range of datasets when paired with meta-learning.

ANN-based models were satisfactory in ideal setups but experienced degradations when applied to new datasets or alternate imaging modalities. This meta-learning-based hybridization was essential because previous ANN-based models did not possess the capacity to learn from changing data conditions. This made the hybrid particularly useful for practical applications, where models need to continue working well across hospitals and patient populations. Through the incorporation of meta-learning, the ANN became capable of handling different tasks and domains, minimizing dataset-specific noise and enhancing generalizability across different clinical environments.

The novelty in this meta-learning hybrid is its ability to overcome the rigidity of conventional ANN architecture. Before its invention, the previous cancer classifiers developed using the ANN were prone to the need for manual hyperparameter selection and thus were not accurate enough when presented with data from different hospitals or different imaging instruments. Meta-learning was instrumental in the development of the model, enabling the model to change its architecture and parameters dynamically. In effect, the meta-learning hybrid developed the trick to learn. Mostly, its freedom from the vulnerability of a sharp change in domains is a major drawback when applying AI in actual clinical applications.

In the year 2024, ELM used a single hidden layer with some random weight value and processing power of output weights, resulting a increase in the speed of the training. Similarly, CNN models were used to gather high level spatial features from imaging techniques like mammography and ultrasound. These changes resulted in a hybrid model which had the CNN's deep feature learning and also ELM's processing efficiency, thus making it perfect for real time clinical applications.[30]

As CNN uses backpropagation to gather deep successive features from medical images like mammography and ultrasound, it is time consuming and a complex process in a whole. The CNN+ ELM hybrid model was a solution to the desperate need for quicker and precise systems as ELM's offer a simple solution using one hidden layer and some random weight value and computationally understood output weights which resulted in the increase in the speed of the training.

The CNN+ELM model was able to draw a difference between benign and malignant cases as it understood simple characteristics of tissue density and tumour structure. The ELM model reached faster computational capabilities of calculating output weights as the features were directly inserted into a ELM classifier rather than through a fully connected model trained using backpropagation method. That's why in 2024 it is used to gather high level spatial features and other information from various medical images as it offered shorter training time and processing cost without affecting on precise detections

The model offered almost instant classification after feature extraction and was special because it supported high sensitivity and specificity of deep learning. The CNN+ ELM hybrid model came with a plus point of applicability of real time and it was a gift in the field of medical applications because in places where processing hardware is limited, model which can train and predict faster are necessary.

Earlier the complexity of CNN models in terms of processing was severe and not fit for field applications as it used backpropagation training methods. Scientists were able to offer a in-between road between feature fullness and processing power using the CNN+ ELM hybrid model as the ELM could not withdraw powerful features from raw unlabelled data. Hence making a model that was the best fit for medical applications.

Classical CNN+ SoftMax models had a large processing overhead and used time consuming looping techniques making it precise but unfit for field applications. The model combines the special features of CNN with the processing power accuracy of ELM's.

In hospitals, the most critical factor is speed and through interchanging of features, the training speed increased greatly without affecting the precision. Unlike previous CNN-SVM hybrid models, the design of CNN+ ELM offered a much higher precision and performance, offering to be the best fit for field applications.[31]

In 2024 in a lung cancer study, feature extraction is performed through CNN, YOLO is used for locating the region, and DCGAN is used making artificial CT scans to overcome class variability. Just like that YOLOv5 is used for tumour detection, MedSAM is used for segmenting the data, and lastly edRVFL is used for classification of data in a 2024 model for breast cancer. The models are joined together offered a precise location of diseases area to perform detection, and classification while increasing dataset availability. Through this process, the presence of false positives can be detected and removed which showed a glance of its processing power. [4]

The most complex hybrid models category consisted of multi-stage ensemble deep learning architectures. Herein, multiple models are extensively integrated/combined and then effectively used to address a number of challenges entailed in tasks for medical image analysis. For instance, in the year 2024, a hybrid model ensemble for the cure of breast cancer was proposed. This model entailed a total of four components. The first entailed the use of YOLOv5 models for rapid detection of the tumours. The second involved the use of MedSAM models for the accurate and minute segmentation of the suspected regions. The third model involved the use of CNN models for the hierarchical features. The fourth model entailed the use of edRVFL models for the final classification. The individual models were selected based on the specific role played in the diagnosis process. Herein, the use of YOLOv5 models was for the accurate placement of the tumours. Moreover, MedSAM models were employed for the segmentation of the boundaries in terms of the minute pixel-wise demarcation. Additionally, the use of CNN models played a vital role in the discriminative features of the images. Finally, the edRVFL model's role was in the prevention of overfitting [30][32].

To make artificial CT scans, DCGAN is used in a hybrid lung cancer model; also YOLO is used for locating the diseased area. The addition of DCGAN helped to bypass dataset variability, which was a major problem as there were large numbers of false positives. That's why this model offered the advantage of including every stage in a particular system [4].

Table 1: Summary of Existing Literature on Hybrid Model-Based Cancer Detection Techniques

Year	Author	Title	Key Findings	Limitations	Future Scope
2018	Abed, Baraa M., et al [26]	Hybrid Breast Cancer Classification (SVM + KNN)	Combined SVM (global boundary learning) with KNN (local classification). Improved accuracy, sensitivity, specificity, and F1-score vs standalone models.	Dependent on feature quality and preprocessing; may struggle with large datasets.	Explore scalability to larger datasets and integration with real-time diagnostic tools.
2021	Jebarani, P. Esther, et al [25]	Hybrid K-Means + GMM for Breast Cancer Detection	K-Means clustered tumor patterns; GMM refined boundaries probabilistically. Improved accuracy and robustness with outlier analysis.	Sensitive to number of clusters and initialization; requires careful tuning.	Apply to multimodal datasets (clinical + imaging) and automate cluster optimization.
2022	Wang, Xiaomei, et al [29]	Intelligent Hybrid Deep Learning Model for Breast Cancer (CNN + GRU)	CNN extracted spatial features, GRU captured sequential dependencies. Achieved higher robustness and representation power.	Computationally expensive; requires large imaging datasets.	Deploy lightweight CNN-GRU models for real-time clinical use.
2022	Han, Luyao, and Zhixiang Yin. [11, 12]	Hybrid Breast Cancer Classification with Meta-learning + ANN	Meta-learning optimized ANN parameters dynamically. Improved adaptability and classification accuracy.	Complexity in training; risk of overfitting small datasets.	Expand meta-learning across multiple cancer types; integrate federated learning.
2022	Lilhore, Umesh Kumar, et al [1]	Hybrid Cervical Cancer Detection (Boruta + SVM/Others)	Boruta selected relevant features; SVM classified with high accuracy. Ensemble compared classifiers.	Focused only on cervical cancer; limited generalization.	Extend Boruta + ML framework for other cancer datasets.

2024	Zarif, Sameh, et al. [7]	Using Hybrid Pre-trained Models for Breast Cancer Detection (CNN + EfficientNet variants)	Transfer learning leveraged CNN + EfficientNet features. Improved generalization and detection performance.	Needs large GPU resources; prone to overfitting without augmentation.	Develop lightweight EfficientNet hybrids for mobile/edge devices.
2024	Sureshkumar, Vidhushavarshini, et al. [31]	Breast Cancer Detection using CNN + Extreme Learning Machine (HCPELM)	CNN extracted features, ELM classified efficiently. Achieved speed and accuracy improvements.	Limited interpretab-ility of ELM; perform-ance depends on CNN quality.	Enhance explainability of CNN+ELM; apply to large-scale datasets.
2024	Qasrawi, Radwan, et al. [30]	Hybrid Ensemble Deep Learning for breast cancer(YOLOv5 + MedSAM + CNN + edRVFL)	Combined detection (YOLOv5), segmentation (MedSAM), feature extraction (CNN), and ensemble classification (edRVFL). Reduced false positives, improved precision.	Complex pipeline; high computational requirements.	Automate pipeline for clinical workflows; optimize for real-time use.

Table 2 : Summary of the Hybrid ML Model Based Cancer Detection Studies with Datasets and Performance Metrics.

Year	Hybrid Model	Dataset	Accuracy	Disadvantages
2018	SVM + KNN (Breast Cancer Classification) [26]	WDBC (Wisconsin Diagnostic Breast Cancer) – 569 records	99.20%	Dependent on feature quality; computationally expensive for large datasets
2021	K-Means + GMM (Breast Cancer Detection) [25]	MIAS Mammogram Database–322 images	95.50%	Error rate 18.64%; SNR only 13.05 dB; segm-entation sensitive to noise
2022	Boruta + SVM (Cervical Cancer Detection) [1]	Not specified	Best among compared models	Relies heavily on feature selection; needs balanced dataset
2022	CNN + GRU (Breast Cancer Detection) [29]	IDC histopathology dataset (Kaggle,277k patches)	Higher than standalone CNN	Resource-intensive; requires large dataset
2022	Meta-learning ANN (Breast Cancer Classification) [11,12]	WDBC dataset – 569 samples (SMOTE balanced)	98.74%	Complex stacking; needs large dataset
2022	CNN + LSTM (Breast Cancer Detection) [29]	IDC histopathology dataset (Kaggle)	Higher than standalone CNN	Resource-intensive; requires large dataset
2024	CNN + YOLOv8 (Lung Cancer Detection) [2]	CT scans synthetic images (DCGAN)	97.67% (CNN), +10% with DCGAN	GAN may create artifacts; YOLOv8 is heavy
2024	Custom CNN + EfficientNetV2B3 (Breast Cancer Detection) [27]	Histopathology (Kaggle, 277k images)	96.30%	Transfer learning may not generalize; complex pipeline

2024	YOLOv5 + MedSAM + EdRVFL + CNNs (Breast Cancer Detection) [30]	Breast ultrasound (Dunya Women's Cancer Center, 4,103 images)	96% (benign), 98% (malignant)	Deployment complex; high computational needs
2024	CNN + LSTM (Lung Cancer Detection) [4]	X-ray & CT scans (128×128, 256×256)	95.47% (X-ray), 99.04% (CT scans)	Needs high-quality CT; real-world noise issues
2025	Logistic Regression + Class Balancing (Breast Cancer Detection) [3]	Not specified	92.98% (Hybrid); 98.57% (ANN best standalone)	Lower than DL; prone to imbalance
2025	AZL Ensemble (AlexNet + ZiNet + LeNet) (Cervical Cancer Detection) [5]	Not specified	99.92%	May overfit; resource-heavy
2025	Hybrid Deep + Handcrafted Features (ResNet-50 + DINOv2) (Mammogram) [9]	CBIS-DDSM mammogram dataset	AUC 79.6%	Lower than DL-only; fusion complexity
2025	Random Forest + CNN (Breast Cancer Detection) [3]	WDBC dataset	High (not exact)	RF feature selection dataset-dependent; CNN may misinterpret irrelevant features

3. Results

So, after reviewing all above studies on hybrid models we reached to the result that Hybrid machine leaning along with deep learning models are far better in performance than the single models of cancer detection. These architectures have surpassed old traditional cancer detection methods repeatedly. These models work on different algorithm altogether achieving high accuracy in cancer detection at an early stage may it be breast, lungs, brain or skin. The precision of these models is very high nearly 95-99%. For example, the SVM-KNN model developed in 2018 has given accurate result up to 99.2% on WBDC dataset, similarly the accuracy of 95.5% is achieved by K-Means +GMM (a 2021 model) on mammogram datasets of MIAS. Generalizations were improved by using combinations of CNN-GRU/LSTM on histopathological dataset of IDC. Boruta +SVM and AZL ensembles achieved strong results in detecting Cervical cancer while in lung cancer the same was achieved by using CNN + YOLOv8 with the dataset of DCGAN augmentation which resulted in a accuracy of 97.67%. The hybrid models like CNN +LSTM also achieved nearly 99.04% accuracy on CT scan datasets. Finally, these hybrid models have many advantages as stated above but some disadvantages too like risk of overfitting, large dataset requirements and high computational power [32, 33].

In general, hybrid models nearly achieve 95 to 99% accuracy in cancer detection, which is better than single ML models and other traditional methods of cancer detection. Hybrid models generally have high accuracy but lack in certain areas, such as generalization, slow training speed, and the requirement for high computational power. The performance of a hybrid model is mainly dependent on the dataset quality, i.e., if the dataset is large, accurate, well-developed, noise-free, etc. Accurate results were produced by using datasets like WDBC, MIAS, IDC, and CBIS-DDSM, while smaller or undefined datasets lead to overfitting and lower accuracy. Because generalization over a variety of datasets, populations, and privacy concerns frequently results in lower accuracy and data overfitting, applying these hybrid models in real-life scenarios is also a difficult problem. Hybrid models, on the other hand, offer us a way forward in advanced cancer detection research, and their performance adaptability across a variety of clinical datasets and real-world settings will be enhanced over time [34].

As a whole, the analysis shows the hybrid models' accuracy ranging between 95% to 99% compared to individual models or conventional statistical approaches. The choice of the datasets in the aspects of accuracy level also played a pivotal role; the datasets denoted by WDBC, MIAS, IDC, and CBIS-DDSM, being properly documented and consisting of ample amounts of data in each category of the research, provided actual accuracy levels; the smaller or indefinite datasets generally exposed the accuracy level despite being hampered by the overfitting phenomenon. Additionally, the SMOTE or GANs [17] techniques generally enhanced the models' ability to be generalized well in the context of a potential overlook concerning the bias making in the artificially created components' aspects [25, 26]. The hybrid models in the research papers used to date be having the potentiality of providing the highest accuracy level but also include a number of intrinsic limitations in their bodies. The complexity level in the computation processes or the potential level being reduced in the overall interpretability in the context of the multi-step models in the research papers predominantly used generally increased. Further, they are also having the potentiality of being questionable in a clinical practice context in terms of a potential overlook either in the aspects of generalization or in the context of being sensitive in the aspects of data privacy or in the context of being utmost in the aspects of the need for large-scale datasets.

On the flip side, the data presented below indicates exciting prospects for hybrid models regarding cancer detection research or related topics with improved accuracy performance levels.

Hybrid imaging techniques with sensors and imaging systems focus on integrating various imaging modalities for better imaging and diagnostic and intraoperative procedures. Dual-Labeled PET and NIR probes (2010) [22], for example, assisted with biphasic imaging of tumors. Intraoperative ultrasound with fluorescence of ICG (2012) assisted with improved imaging of liver metastasis. Again, HyMaP imaging segmentation (2013) combined magnitude and phase imaging for improved histological imaging of samples. NBI imaging with FICE and CLE imaging techniques (2014) assisted with improved imaging of early-stage gastric cancer. On the other hand, Quantitative Ultrasound imaging techniques (2015) showed very good correlation with stages of cancer in prostrate nodes. Very recently, Two-stage ML with CNN Segmentation imaging techniques of Ultrasound imaging (2021) helped with simultaneous localization and identification of tumors.

Overall, these approaches illustrate how combining complementary imaging technologies improves sensitivity, minimizes false negatives, and facilitates improved clinical choice. Still, there are limitations—like small datasets, operator dependence, and invasive procedures—which underscore the necessity of future advancements on scalability, automation, and AI-enhanced interpretation.
Hybrid methodologies for the diagnosis of cancer can be classified into sensor hybrids and machine learning/deep learning hybrids. These sensor hybrids have applied the complementary strengths of different sensors in view for better visualization and diagnosis

of cancer. For example, some researchers used NIR contrast agents for PET imaging and enabled multisite visualization of tumors. Others used intraoperative ultrasound imaging in ICG fluorescence and allowed for better visualization during surgery. Other methodologies that have employed HyMaP segmentation for histological imaging, multimodal endoscopy, among others, for better visualization of cancers but were largely characterized by having very small population size, invasive, and human-dependent.

Contrary to this, the hybrids of ML/DL incorporate various algorithms together to improve the resistance level of classification. The simple hybrids involve a combination of SVM + KNN and K-Means + GMM, which resulted in an improvement in the confidence level. Meanwhile, hybrids involve the combination of Boruta [1] + SVM for removing redundancies that result in feature reduction. Advanced hybrids are inclusive of CNN + GRU, CNN + LSTM, CNN + EfficientNet [27], and combination models that include YOLOv5 + MedSAM + edRVFL, that resulted in high accuracy for breast, cervical, and lung cancers with a percentage value of 95-99% accuracy. It also has some limitations with respect to high computation cost, imbalance in classes, and risks of occurrence of overfitting [4]. These two categories above depict the power of hybridization to attain accuracy in cancer identification and make it imperative to look for a solution that solves scalability, with understandability, having remained medicinally validated.

Table 3: Summary of the Hybrid Methods Using Sensors

Year	Hybrid Model	Dataset	Accuracy	Disadvantages
2010	PET + NIR (Dual-labeled Trastuzumab Probe) [22]	HER-2 positive breast cancer cell lines + mice models	Not reported	Limited to HER-2+ tumors, preclinical stage
2012	Intraoperative Ultrasound (IOUS) + ICG Fluorescence Imaging [20]	25 colorectal cancer patients with liver metastases	Not reported	Invasive procedure, requires specialized surgical equipment
2013	HyMaP (Hybrid Magnitude-Phase Segmentation) [21]	MITOS dataset (55 histology images)	F1 = 0.89	Very small dataset, limited generalization
2014	Multi-modal Endoscopy (NBIFICE, I-scan, MEAFI + CLE) [2][10]	Early gastric cancer (clinical endoscopy images)	Not reported	Lower performance in multi-class classification, overfitting
2015	Quantitative Ultrasound Spectroscopy (QUS) [23]	15 prostate cancer patients (volumetric ultrasound)	0.764 (correlation, not accuracy)	Lower performance in multi-class classification, overfitting

4. Conclusions

This systematic review examined recent advances in hybrid computational models for early cancer detection. The analysis of the selected studies indicates that hybrid approaches consistently outperform single model methods. Hybrid artificial intelligence models represent a highly promising direction for early cancer detection. With continued improvements in data quality, interpretability, and clinical validation, these approaches have the potential to enable affordable, rapid, and accurate early cancer detection, ultimately improving patient outcomes and advancing precision medicine.

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