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Cancer Disease Identification and Recommendation Using Hybrid Deep Learning Algorithms

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Abstract

It presents an automated system for cancer identification and classification using MATLAB, focusing on three types of cancer: brain tumour, skin cancer, and lung cancer. The system leverages advanced image processing techniques for cancer detection, feature extraction, and image segmentation to isolate cancerous regions in medical images. The core of the system is a Convolutional Neural Network (CNN), which is trained to predict the presence of cancer based on the extracted features. Feature selection methods are applied to reduce the complexity of the data, ensuring the CNN focuses on the most relevant characteristics of the suspected cancerous regions. The classification output not only confirms the presence of cancer but also distinguishes between different types of cancer, such as brain tumours, skin cancer, or lung cancer. Upon successful classification, the system provides medical recommendations, guiding clinicians toward appropriate next steps in diagnosis or treatment. This project aims to enhance cancer detection accuracy and efficiency, providing a non-invasive, automated solution to assist healthcare professionals in making informed decisions, potentially leading to earlier interventions and better patient care outcomes.

1. Introduction

Cancer is a multifaceted disease that impacts millions globally, presenting significant challenges despite remarkable strides in medical science. Early and precise diagnosis is particularly tricky, often involving imaging, biopsies, and genetic tests that, while valuable, can be time-intensive and sometimes insufficient for crafting highly personalized treatment plans. These traditional methods, though widely used, may not always provide the speed or precision needed to keep pace with the disease's complexity. Emerging solutions, however, are offering hope. Artificial intelligence (AI) and deep learning technologies are increasingly stepping into the spotlight, demonstrating immense potential to revolutionize cancer care. By leveraging vast amounts of data, these technologies can enhance diagnostic accuracy, reduce delays, and offer tailored treatment recommendations, transforming patient outcomes in unprecedented ways. Personalized treatment is essential in cancer care, as patients respond differently to various treatments.

1.1. Hybrid Deep Learning Approaches in Cancer Diagnosis

The hybrid model in this approach combines CNNs, known for their effectiveness in image recognition, which are well-suited for sequential data analysis. By using CNNs, the system can analyze and interpret medical images like MRI or CT scans, identifying cancerous lesions and assessing their severity. In parallel, RNNs analyze sequential data, such as patient medical histories which are critical in understanding each patient's unique risk factors and disease progression. This multi-layered approach allows the model to perform detailed cancer classification, categorizing cases by type and stage more accurately than traditional models alone. It integrating traditional machine learning techniques adds a layer of interpretability, helping the model to factor in other patient-specific details and improve prediction accuracy.

1.2. Personalized Treatment Recommendations

Personalized treatment is essential in cancer care, as patients respond differently to various treatments based on their genetic profile, cancer type, and medical history. The hybrid model assesses these individualized factors by analysing a broad dataset of patient outcomes from past cases, evaluating how similar patient profiles responded to particular therapies. As a result, the system can suggest tailored treatment plans that are likely to yield the best clinical outcomes for each patient. This personalization helps optimize treatment efficacy, reduce potential side effects, and improve patient survival rates, ultimately supporting a more effective and patient-centric approach to cancer care.

2. Literature Survey

Y. Qian, Z. Zhang and B. Wang, et al., [1] in their paper ProCDet: A New Method for Prostate Cancer Detection Based on MR Images. The methodology presents an innovative approach to detecting prostate cancer using magnetic resonance (MR) imaging. Prostate cancer, a common malignant tumor in men, poses a unique challenge for imaging-based diagnosis due to its small size and indistinct outlines in MR images. This difficulty is compounded by the limited availability of labeled prostate cancer data, which further complicates the development of accurate detection methods. To address these challenges, the authors propose ProCDet, a three-part methodology that enhances prostate cancer detection. The approach begins with the registration of different MR image sequences to establish spatial relationships, ensuring consistency across imaging modalities. Next, they introduce a specialized prostate segmentation network incorporating an attention mechanism to accurately separate the prostate from background noise. Finally, they apply a 3D segmentation network with a Focal Tversky Loss function to precisely identify and localize cancerous lesions within the prostate. A noteworthy aspect of ProCDet is its use of self-supervised learning, allowing it to leverage unlabeled data, which is often more available, to improve detection accuracy. The ProCDet system was rigorously tested on the ProstateX dataset, where it achieved a true-positive rate of 91.82% with an average of 0.6275 false positives per patient. These results suggest that ProCDet offers a competitive and promising approach for MR image-based prostate cancer detection, with potential applications in clinical settings [1]. J. Omar Bappi, M. A. T. Rony, M. Shariful Islam, S. Alshathri and W. El-Shafai, et al. [2] in their paper A Novel Deep Learning Approach for Accurate Cancer Type and Subtype Identification. The Methodology presented a deep learning (DL) framework for the early and accurate identification of cancer types and subtypes, employing a dataset of over 130,000 cancer-related images. This model utilized hybrid architectures, combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, for classifying eight primary cancer types and 26 subtypes. The model achieved notable accuracy, particularly for lymphoma, setting a new standard in cancer type classification. Their methodology involved two stages of 3 classifications: an initial categorization of primary cancer types, followed by a detailed classification into subtypes. By incorporating X-OR gate-based fusion, the model significantly reduced misclassification rates and enhanced the certainty of predictions. This study demonstrates how hybrid deep learning models can serve as powerful diagnostic tools, achieving high confidence and accuracy, and setting a benchmark for future research in cancer classification [2]. U. Ravindran and C. Gunavathi, et al. [3] in their paper Cancer Disease Prediction Using Integrated Smart Data Augmentation and Capsule Neural Network. The methodology In addressing the issue of limited gene expression data, Ravindran and Gunavathi (2024) developed a cancer prediction model combining data augmentation and Capsule Neural Network (CapsNet) techniques. Their approach involved a smart data augmentation process that integrates Uniform Distributive Augmentation (UDA) and Wasserstein-Generative Adversarial Networks (W-GAN) to increase sample data quality. This novel augmentation strategy allowed for more accurate training of deep learning models, enabling effective prediction of cancer types despite smaller datasets. CapsNet's unique architecture improved classification accuracy by capturing spatial hierarchies of data points, resulting in enhanced diagnostic reliability. By focusing on the correlation-centered selection and feature reduction from gene expression datasets, this model addresses key challenges in gene-based cancer diagnostics. The study's findings show that combining smart data augmentation with deep learning frameworks like CapsNet can lead to classification precision and reduced error rates in cancer detection [3]. A. Das, N. Neelima, K. Deepa and T. Özer, et al. [4] in their paper Gene Selection Based Cancer Classification with Adaptive Optimization Using Deep Learning Architecture. The methodology proposed a robust framework for cancer classification that optimizes gene selection and manages high-dimensional data issues. Leveraging deep learning techniques and the Enhanced Chimp Optimization (ECO) algorithm, their approach effectively minimized redundant data, reducing dimensionality while maintaining critical information for classification. This preprocessing step employed Min-Max Normalization to enhance data quality, followed by a Depth-wise Separable Convolutional Neural Network (DSCNN) for 4 effective classifications. The model's adaptive optimization demonstrated improved resilience against overfitting, yielding a classification accuracy of 99.18% across multiple gene expression datasets. Through optimized feature selection, this study addressed computational and storage constraints often associated with gene expression analysis. The authors' approach highlights the importance of feature reduction and adaptive optimization in enhancing deep learning performance, thereby advancing the accuracy and reliability of gene-based cancer classification models [4]. M. A. Jopek, et al. [5] in their paper Deep Learning-Based, Multiclass Approach to Cancer Classification on Liquid Biopsy Data. The methodology explored a novel approach to cancer classification based on liquid biopsy data, utilizing deep learning (DL) for a less invasive and more efficient diagnostic method. Liquid biopsies analy ze tumor-derived markers in blood, offering a promising alternative to traditional biopsies. The study introduced a DL model that classifies cancer types by analyzing platelet RNA and generating heatmap images, which represent gene expression data across six cancer sites, including ovarian and lung cancers. The model demonstrated an accuracy of 90.5% in distinguishing between cancer types in specific datasets, suggesting high potential for clinical applications. Additionally, the use of explainable artificial intelligence (XAI) highlighted critical genes impacting classification decisions, increasing the transparency and trustworthiness of the DL model in clinical settings. This approach represents a major step in integrating liquid biopsies with DL, offering a less invasive and precise method for early cancer detection [5]. B. K. Sethi, D. Singh, S. K. Rout and S. K. Panda, et al. [6] in their paper Long Short-Term Memory-Deep Belief Network Based Gene Expression Data Analysis for Prostate Cancer Detection and Classification. The methodology developed a deep learning model for prostate cancer (PRC) detection, incorporating an LSTM-DBN structure to process gene expression data. This Gene Expression Data Analysis technique, termed GEDAAI-PCD, integrates the wild horse optimization (EWHO) method for hyperparameter tuning, enhancing the model's precision and recall in classifying prostate cancer samples. By normalizing and optimizing the gene expression data, this method addresses challenges in analyzing complex datasets, such as feature dimensionality and noise. Experimental results on open-access gene databases confirmed that GEDAAI-PCD's approach outperforms standard models in predictive accuracy. The study highlights how deep learning, combined with effective optimization techniques, can be instrumental in cancer diagnostics by improving model performance and predictive accuracy for early prostate cancer detection [6]. M. P. Yong, et al. [7] in their paper Histopathological Cancer Detection Using Intra-Domain Transfer Learning and Ensemble Learning.

The methodology focused on enhancing histopathological cancer detection by employing intra domain transfer learning and ensemble learning. Their study aimed to automate cancer diagnosis using histopathology image datasets, traditionally a manual and error-prone process. By combining convolutional neural networks (CNNs) with transfer learning, their model achieved impressive accuracy on multiple public histopathology datasets, including 99.78% on the GasHisSDB dataset. Ensemble learning further improved the model's ability to identify cancerous features from complex t issue images, outperforming previous methods. This model demonstrates the significant role that DL can play in supporting pathologists by reducing workload and improving diagnostic accuracy. The study's results underscore the potential of transfer and ensemble learning to handle large, complex datasets, making histopathology-based cancer diagnosis more efficient and reliable [7]. A. Farrag, Z. M. Fadlullah, M. M. Fouda and N. S. Almalki, et al. [8] in their paper Survival Based Treatment Planning Using Stage-Specific Machine Learning Models. The methodology tackled the need for more targeted treatment strategies in cancer care through a novel survival-based ML framework. This framework considers patient-specific cancer stages, using stage-specific machine learning models to predict optimal treatment combinations and survivability outcomes. The two-step approach involved both classification and regression analyses for breast cancer data, where model predictions were guided by balancing strategies. Such tailored predictions aid clinicians in decision-making by providing interpretable recommendations for treatment based on survival probabilities. The study highlighted the limitations of traditional clinical support systems, which often lack survival 6 focused predictive models, and showcased the value of survival analysis in creating comprehensive treatment paths. The results from t experimental evaluations demonstrated how stage-specific ML models can support medical professionals by improving the accuracy of survival estimations, ultimately allowing individualized cancer treatment [8]. A. Imran, A. Nasir, M. Bilal, G. Sun, A. Alzahrani and A. Almuhaimeed, et al. [9] in their paper Skin Cancer Detection Using Combined Decision of Deep Learners. This ensemble approach leveraged the unique strengths of each model, yielding superior diagnostic accuracy, sensitivity, and specificity compared to individual models. The study addressed the challenges in skin cancer detection, particularly in identifying melanoma, by using the ISIC dataset and combining predictions from individual learners for improved reliability. By enhancing sensitivity and reducing false negatives, the ensemble model demonstrated potential in clinical applications where precision is critical. Their work underscores the effectiveness of ensemble learning in medical image analysis, providing a reliable diagnostic tool that leverages the combined expertise of multiple DL models, thereby improving diagnostic performance in detecting skin cancers [9]. F. Alrowais, K. Mahmood, S. S. Alotaibi, M. A. Hamza, R. Marzouk and A. Mohamed, et al. [10] in their paper Laryngeal Cancer Detection and Classification Using Aquila Optimization Algorithm with Deep Learning on Throat Region Images. The methodology introduced an innovative deep learning framework for laryngeal cancer detection, utilizing the Aquila Optimization Algorithm (AOA) to fine-tune a Deep Belief Network (DBN) on throat region images. This approach leverages the Inceptionv3 model for feature extraction, providing high precision and recall in cancer classification. The AOA's hyperparameter tuning enables more accurate classification of cancerous tissues, outperforming traditional models in terms of diagnostic metrics. Their findings suggest that combining AOA with deep learning models such as DBN can significantly enhance detection accuracy. The study's focus on optimizing deep learning models for medical imaging has broader implications, showing how advanced optimization algorithms like AOA can support clinical decision-making by providing reliable diagnostic tools for complex cancer types [10] P. A. ME, M. K. Devi, N. N. Jose, V. G, R. M. Sharma and G. K. Yadav, et al. [11] in their paper Stacked Deep Learning Integrated with the Sparrow Search Algorithm for Medical Image Analysis. The methodology introduced a hybrid approach for pancreatic cancer classification, integrating stacked deep learning with the Sparrow Search Algorithm (SSA) for optimization. Pancreatic cancer, challenging to detect and diagnose, often requires high sensitivity and specificity in imaging analysis. Their approach combined SSA with deep learning, where SSA optimized classification processes, allowing the model to learn complex features in medical images. This combined model showed substantial improvement in accuracy and specificity in classifying pancreatic cancer. Their work demonstrated that integrating optimization algorithms with deep learning frameworks could enhance diagnostic reliability and enable early detection. By refining pancreatic cancer classification, this hybrid approach offers new potential for improving survival rates and developing individualized treatment plans, showcasing how AI-driven optimization can lead to more effective diagnostic models in cancer research [11]. M. Subramanian, J. Cho, V. E. Sathishkumar and O. S. Naren, et al. [12] in their paper Multiple Types of Cancer Classification Using CT/MRI Images Based on Learning Without Forgetting Powered Deep Learning Models. The methodology focused on transfer learning models, applying pre-trained Convolutional Neural Networks (CNNs) like VGGNet and DenseNet for the classification of multiple cancer types. Their model harnessed "Learning without Forgetting" (LwF) to prevent the loss of previous classification capabilities when training on new cancer datasets. This method allowed the model to retain and apply previously learned knowledge, which enhanced its adaptability across diverse cancer types, including lung and brain cancers. The study employed Bayesian optimization to determine optimal hyperparameters, further improving classification accuracy. Experimental results showed that transfer learning effectively streamlined model training, yielding faster and more accurate predictions than traditional methods. The study's findings underscore the potential of LwF in preserving model capabilities 8 across varied datasets, making this approach promising for large scale cancer diagnostic applications in real-world clinical settings [12]. U. Naseem, et al. [13] in their paper An Automatic Detection of Breast Cancer Diagnosis and Prognosis Based on Machine Learning Using Ensemble of Classifiers. The methodology investigated breast cancer (BC) detection using an ensemble learning model, which combined several ML classifiers to improve diagnostic accuracy. They evaluated various machine learning techniques, including artificial neural networks (ANNs), alongside ensemble models to achieve higher prediction accuracy in BC classification. Their analysis on two benchmark datasets showed that ensemble models provided a robust approach for prognosis by compensating for class imbalances in data, a common challenge in breast cancer diagnosis. Additionally, the study demonstrated that applying balanced class weights improved model stability and performance. With an overall accuracy rate of 98.83%, this study highlighted the effectiveness ensemble learning in improving diagnostic reliability. Ensemble learning's high performance is beneficial in medical applications where accurate, consistent results are critical to patient care, especially for complex diseases like breast cancer [13]. S. Iqbal, et al. [14] in their paper Prostate Cancer Detection Using Deep Learning and Traditional Techniques. This research highlighted the limitations of traditional feature extraction, which relies heavily on hand-crafted features that are labor intensive. By contrast, the deep learning approach enabled automated feature extraction, achieving high sensitivity and specificity for prostate cancer detection. Their model employed both LSTM and ResNet-101 to enhance accuracy, with the latter achieving perfect accuracy and AUC values, indicating a clear advantage over non-deep learning methods. The study further demonstrated that ResNet-101's advanced architecture could capture complex patterns in carcinoma images, offering substantial improvements over conventional diagnostic techniques. This work underscores the potential of combining deep learning with traditional diagnostic methods to enhance the precision of prostate cancer diagnosis [14]. R. Ashraf, et al. [15] in their paper Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection. The methodology addressed the challenge of detecting melanoma, a severe form of skin cancer, by developing a region-of-interest (ROI) transfer learning model. Melanoma diagnosis often involves visual challenges due to similarities with benign skin lesions. This study utilized an improved k-means algorithm to extract critical ROI features, enhancing the model's accuracy in differentiating between melanoma and nevus images. Using CNNs and transfer learning with data augmentation on two skin cancer datasets, DermIS and DermQuest, the model achieved over 97% accuracy in melanoma detection. By focusing on specific regions of images, the model improved feature extraction and training efficiency, addressing limitations in previous systems that used full-image approaches. The ROI-based model demonstrated that targeted image analysis can significantly improve diagnostic accuracy, marking a promising development in skin cancer detection using deep learning [15] Table 1 shows Comparative Table.

3. Comparative Table

Table 1 Comparative Table

S.No	Methodology	Dataset Used	Merits	Demerits	Application
[1]	ProCDet combines MR image registration, attention-based prostate segmentation, and 3D lesion segmentation with Focal Tversky Loss.microarray and RNA-Seq	ProstateX .	High true-positive rate, uses self-supervised learning to improve accuracy with unlabeled data.	Limited by availability of MR imaging data.	Clinical prostate cancer detection using MR images.
[2]	Developed a deep learning model using CNNs, KNN, SVM, and LSTM for cancer classification	Kaggle cancer images.	Achieved high accuracy rates of 99.25% for primary classes and 97.80% for subclasses.	Model complexity may hinder real-time application and require significant computational resources.	Enhances cancer diagnosis.
[3]	This research utilizes correlation-centered feature selection and a smart data augmentation process using CapsNet for cancer classification.	Gene expression datasets.	Achieved over 98% accuracy, precision, and recall, significantly improving classification outcomes and reducing error rates in cancer diagnosis.	The need for extensive computational resources and potential biases in synthetic data generation may limit practical applicability.	Improves cancer diagnosis.
[4]	The study uses deep learning with data augmentation and the Enhanced Chimp Optimization algorithm for gene selection.	Augmented gene datasets.	Achieved 99.18% accuracy with improved precision, recall, and F1 score, enhancing cancer classification performance significantly.	Potential challenges include high computational resource demands and possible overfitting despite optimization efforts.	Enhances cancer identification
[5]	This study employs deep learning to analyze blood platelet RNA and classify multiple cancer types using heatmap images.	Blood cancer samples.	Achieves up to 90.5% balanced accuracy on specific cancer origin detection, showcasing deep learning's effectiveness in diagnostics.	Balanced accuracy of 66.51% suggests limitations in distinguishing between closely related cancer types, needing further refinement.	Enables personalized detection.
[6]	This study uses the GEDAAI-PCD method, combining LSTM-DBN and	Prostate gene database	The GEDAAI-PCD method improves classification	Challenges include complex hyperparameter	Prostate cancer detection.

	Enhanced Wild Horse Optimization for prostate cancer classification.		accuracy, showing strong potential in prostate cancer detection and diagnostic support.	tuning and high computational demands due to LSTM-DBN model optimization.	
[7]	This study employs deep learning models using intra-domain transfer learning and ensemble learning techniques to analyse histopathology images.	Public histopatho logy datasets.	Achieved state-of-the-art accuracy levels, enhancing histopathology image analysis and supporting early cancer detection.	Challenges remain in extracting comprehensive features from histopathological images, particularly with low-resolution inputs.	Enhances diagnostic efficiency.
[8]	The study uses a two-step approach with machine learning models to classify and analyze survival outcomes based on treatment data.	Real breast cancer dataset.	This system enhances decision-making by offering tailored treatment recommendations that are informed by individual survival predictions.	One limitation is the dependence on historical data, which may not fully reflect recent advances in treatment or the diversity of patients.	Personalized treatment planning.
[9]	An ensemble model combining VGG, CapsNet, and ResNet deep learners is developed for skin cancer detection, improving predictive accuracy.	ISIC public dataset.	Enhanced accuracy through ensemble learning.	Computationally intensive. Requires diverse, well-labeled data.	Accurate skin cancer detection.
[10]	The study introduces the LCDC-AOADL technique, combining Inceptionv3 and DBN with Aquila Optimization for laryngeal cancer detection.	Laryngeal cancer dataset.	Achieves high accuracy (96.02%) and precision, improving detection rates for early and precise laryngeal cancer diagnosis.	High computational demands and model complexity may limit accessibility and real-time application in clinical settings.	Enhances laryngeal detection.
[11]	SSASDL-PCDC uses a Sparrow Search Algorithm (SSA) for CNN-BiLSTM hyperparameter tuning, with DenseNet and Harris Hawks Optimization (HHO) for feature extraction on CT images.	Comprehe nsive database of pancreatic CT images.	High sensitivity, specificity, and accuracy (99.26%).	Computationally intensive.	Pancreatic cancer diagnosis
[12]	Proposed AI-based deep learning models utilize transfer learning and Learning without Forgetting for cancer image classification.	Cancer type images	Transfer learning enhances classification accuracy, outperforming existing state-of-the-art techniques for cancer detection.	Transfer learning may lead to overfitting on new datasets if not properly managed.	Improves cancer detection.

[13]	The study utilizes machine learning and ensemble classifiers with up-sampling and balanced class weighting for breast cancer detection.	Benchmark breast cancer datasets.	The ensemble method achieved high accuracy of 98.83%, outperforming state-of-the-art models in BC detection.	Potentially limited by computational requirements for training and the need for well-labeled, balanced data.	Enhances breast cancer detection.
[14]	This research employs deep learning techniques using LSTM and ResNet 101 for prostate cancer image analysis and classification.	Prostate cancer images.	Deep learning methods, particularly ResNet 101, significantly outperform traditional classifiers in accuracy and predictive performance.	Deep learning models require substantial computational resources and extensive labelled datasets for effective training and validation.	Enhances prostate detection.
[15]	Improved k-means extracts ROIs from melanoma images; CNN-based transfer learning with data augmentation enhances detection.	DermIS and DermQuest datasets.	Improved melanoma detection accuracy (97.9% DermIS, 97.4% DermQuest).	Complex model design requires expert tuning and computational resources.	Skin cancer screening.

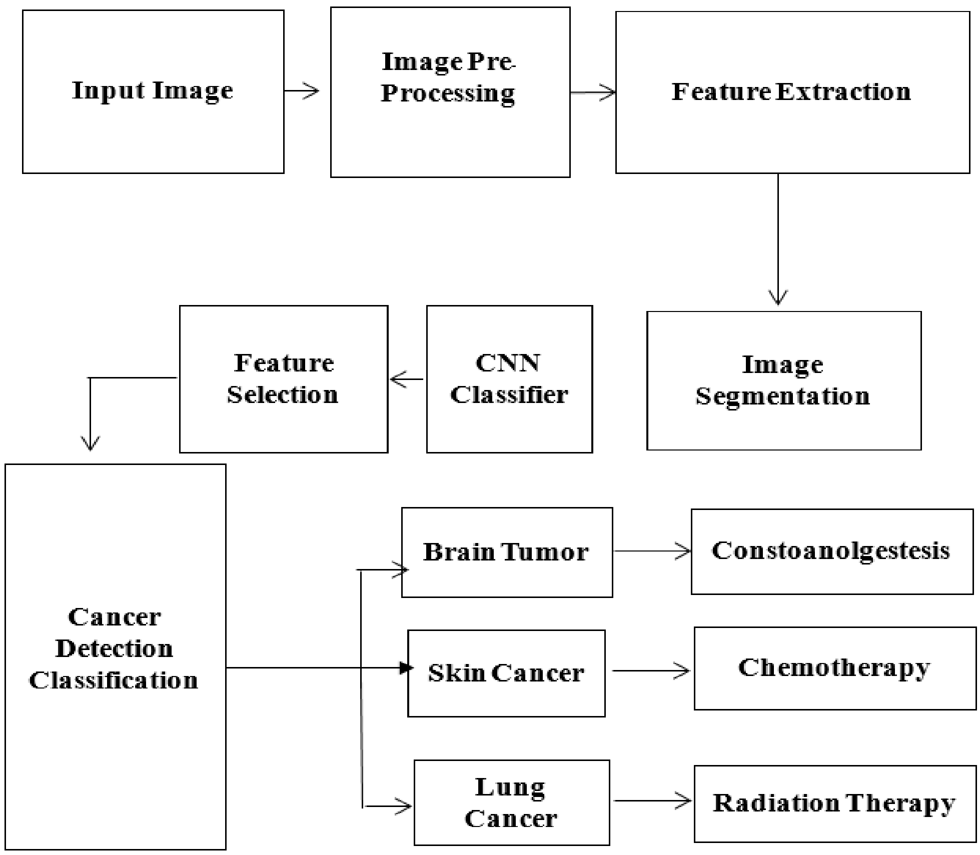

Figure 1 Proposed Block Diagram for Cancer Disease Identification and Recommendation Using Hybrid Deep Learning Algorithms

4. Results and Discussion

4.1. Results

The system integrates image processing, feature extraction, image segmentation, and CNN-based deep learning algorithms to identify and classify cancer types. Additionally, it provides medical recommendations based on the 34 classification results, assisting clinicians in determining the next steps for diagnosis or treatment. Medical images, such as MRI (for brain tumors), dermoscopy (for skin cancer), and CT scans (for lung cancer), are acquired. Features such as texture, shape, and intensity are extracted, as cancerous. Tissues often have distinct patterns and irregular shapes. The CNN comprises convolutional layers that learn the spatial features from the image, pooling layers for down sampling, and fully connected layers for final classification. The model is trained to identify patterns unique to brain tumors, skin cancer, and lung cancer, providing a multi-class classification output. Provide recommendations such as biopsies, specific treatments (chemotherapy, surgery), or further diagnostic tests depending on the cancer type (brain tumor, skin, or lung cancer). Medical recommendations can be provided. Figure 1 shows Proposed Block Diagram for Cancer Disease Identification and Recommendation Using Hybrid Deep Learning Algorithms

4.2. Discussion

In this project, we developed an automated system using MATLAB for detecting and classifying three types of cancer: brain tumors, skin cancer, and lung cancer. By employing image processing techniques, we focused on accurately identifying cancerous regions within medical images, making the detection process more efficient. The system primarily uses a Convolutional Neural Network (CNN), which is trained to recognize patterns specific to each cancer type. The CNN is optimized through feature selection methods that reduce data complexity, allowing the model to focus on the most critical characteristics in identifying cancer. A unique aspect of this system is its ability not only to detect cancer presence but also to differentiate among the specific types. This can provide clinicians with critical insights into the diagnosis.

Furthermore, after a successful classification, the system offers preliminary medical recommendations, guiding healthcare professionals in planning the next diagnostic or treatment steps. This project contributes to cancer diagnostics by offering a non-invasive, efficient, and accurate tool, potentially leading to earlier intervention and improved patient care. By enhancing diagnostic accuracy, this system supports healthcare professionals, aiding them in making informed decisions that could positively impact patient outcomes.

Conclusion

The system not only detects cancer but also provides personalized medical recommendations based on the classification results, which help guide healthcare professionals in deciding on further diagnostic tests or treatment options. By combining automation with high accuracy, this tool supports early cancer detection and reduces diagnostic errors, allowing clinicians to make more precise, informed decisions. Its versatility in handling various cancer types such as brain, skin, and lung cancers enhances its value as a reliable diagnostic aid across different medical cases. Ultimately, this system has significant potential to improve patient outcomes by facilitating faster and more accurate diagnoses, helping clinicians respond quickly and confidently. With personalized recommendations, the system supports patient-centered care, enabling tailored treatment strategies that contribute to better, more effective healthcare.

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