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An AI-Based Framework for Early Cancer Detection Using Machine Learning Technique

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ABSTRACT

Cancer detection using machine learning has emerged as a promising approach for improving early diagnosis and patient outcomes. This research focuses on applying advanced algorithms such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and ensemble models to analyze medical imaging and histopathological data. The system automates feature extraction and classification, enhancing diagnostic accuracy and reducing human error. Data from breast, lung, and oral cancer datasets were used for model training and validation. Preprocessing techniques were applied to ensure image clarity and consistency. The proposed model achieved high precision and recall in identifying cancerous patterns. Limitations include data imbalance and interpretability challenges. Future work aims to integrate real-time diagnostics and multi-modal data for broader clinical use.

Keywords: *Cancer Detection, Machine Learning, Deep Learning, CNN, SVM, Medical Imaging, Early Diagnosis, AI in Healthcare.*

1. INTRODUCTION

Cancer is one of the leading causes of death globally, with millions of new cases reported each year. Early detection and accurate diagnosis are critical for effective treatment and improved survival rates. Traditional diagnostic methods such as biopsy, radiology, and manual image interpretation are time-consuming and often prone to human error. With the rapid advancement in artificial intelligence, machine learning (ML) has emerged as a transformative tool in medical diagnostics. Machine learning algorithms can analyze vast amounts of complex data with high speed and precision, aiding in early cancer detection. Among various techniques, Convolutional Neural Networks (CNNs) are especially effective in medical image classification tasks. These models automatically extract features from imaging data, reducing the need for manual intervention. Support Vector Machines (SVM), Decision Trees, and ensemble methods are also widely used for tumor classification and risk prediction. Researchers have applied ML to detect different cancer types, including breast, lung, oral, prostate, and skin cancer. Studies from 2021– 2025 report remarkable improvements in diagnostic accuracy using AI-driven models. In particular, deep learning frameworks have outperformed traditional diagnostic systems in image analysis. However, challenges such as limited annotated datasets, overfitting, and lack of model explainability still persist. To overcome these, researchers are integrating hybrid models and using techniques like data augmentation and transfer learning. The goal is to build intelligent systems capable of real-time analysis and clinical decision support. Machine learning can also help in identifying cancer stages, predicting patient outcomes, and personalizing treatment plans. Moreover, ML models can assist healthcare professionals in reducing workload and minimizing diagnostic errors. This paper explores the use of ML algorithms in detecting cancer, comparing different models and datasets. We focus on evaluating their performance in terms of accuracy, precision, recall, and computational efficiency.

2. LITERATURE REVIEW

TABLE-1

Author(s) & Year	Topic	Algorithms Used	Accuracy / Metrics	Limitations	Key Findings / Results
Gizem Tanriver et al. (2021)	Oral Lesion & OPMD Detection	U-Net, Mask R-CNN, YOLOv5, EfficientNet-b4/b7	Dice: 0.929 (U-Net), YOLOv5l AP50: 0.951, F1: 0.858 (EffNet-b4)	Small and diverse dataset, misclassification of benign lesions	Effective, real-time model for self-screening and primary care apps
Dr. Sabin	Periodontal Health	SPSS statistical	Statistically	No direct	Beedi smokers and

Author(s) & Year	Topic	Algorithms Used	Accuracy / Metrics	Limitations	Key Findings / Results
Siddique et al. (2025)	in Tobacco Users	analysis	significant ($p < 0.0005$) for CPI & LOA	correlation with nicotine levels	mixed users have the worst periodontal outcomes
Jérôme de Chauveron et al. (2024)	AI in Oral SCC via Photographs	VGG-19, ResNet, EfficientNet, ISSA, SVM	Accuracy up to 99%, Sensitivity > 95%	Lack of large, verified datasets	Ensemble & attention models are promising; standard datasets needed
Momina Meer et al. (2024)	OSCC via Histopathological Images	MobileNet-V2 + DarkNet-19, CCA, QWOA	99% (100×), 98.7% (400×)	Limited resolution and dataset size	Hybrid model outperforms traditional methods
Arslan Khalid et al. (2023)	Breast Cancer Detection	RF, DT, KNN, LR, SVC, CNN	RF Accuracy: 96.49%	Deep learning requires high computation; MRI is expensive	RF most efficient; early detection improves outcomes
Vinay V. et al. (2025)	AI in Oral Cancer (Review)	CNN, SVM, EfficientNet, Swin Transformer, XGBoost	CNN: 96.76%, Histopathology model: 99.65%	Dataset imbalance, lack of standardization, privacy issues	AI greatly improves diagnosis/prognosis; integration needs validation
Basem S. Abunasser et al. (2022)	Breast Cancer with Xception	Xception + GAN	Accuracy: 97.60%, F1: 97.58%	GAN may add bias; no clinical/genetic data used	Strong classifier for 8 subtypes; promising for real-world deployment
Sweta Bhise et al. (2021)	Breast Cancer via ML	CNN, SVM, RF, KNN, LR, Naïve Bayes	CNN: ~97.3%, ANN: 99.3% (referenced)	CNN needs large datasets & computing power	CNN best for image-based detection; real-world clinical potential
Sri Hari Nallamala et al. (2019)	Breast Cancer via Ensemble ML	LR, NN, SVM + Ensemble Voting	Accuracy: 98.5%	Focus on structured data; limited features	Ensemble improves predictions; good for decision support systems
Liangbo Li et al. (2024)	Oral Cancer via Endoscope Images	U-Net + ResNet-34	Dice: 0.80, IoU: 0.70, Precision: 0.96, Recall: 1.00	Overfitting, small dataset, low early-stage detection	Portable device with strong precision; potential for low-resource areas

TABLE-2

Author & Year	Title/Topic	Dataset Used	Algorithms Used	Accuracy	Key Findings	Limitations
Muhammet Fatih Ak (2020)	Breast Cancer Detection via Data Visualization & ML	Wisconsin Breast Cancer Dataset	Logistic Regression, KNN, SVM, Naïve Bayes, Decision Tree, Random Forest, Rotation Forest	Logistic Regression: **98.1%**	Simple models (like LR) with proper preprocessing and visualization outperformed complex ones; visualization aids in better feature selection.	Imbalanced dataset, lack of external validation, some features removed due to outliers, may limit generalizability.
Siham A. Mohammed et al. (2020)	Analysis of Breast Cancer Detection Using ML	WBC & Breast Cancer Datasets	J48 (C4.5), Naïve Bayes, SMO (SVM variant)	SMO: **99.56%**, J48: **98.20%**	Preprocessing (resampling, discretization, outlier/missing value handling) significantly improved classification performance.	Limited datasets (only 2), no deep learning, no external validation, focused on structured data only.

Author & Year	Title/Topic	Dataset Used	Algorithms Used	Accuracy	Key Findings	Limitations
Muawia A. Elsadig et al. (2023)	Comparative Study of ML Classifiers for Breast Cancer Detection	Enhanced WBCD	LR, DT, KNN, NB, RF, MLP, SVM, Stacking Ensemble	SVM: **97.7%**, MLP: **96.8%**	SVM outperformed all models after feature selection; deep feature weighting and selection were critical. Ensemble (Stacking) also performed well.	Single dataset used, deep learning/image features not explored, limited generalizability.
Monika et al. (2020)	Skin Cancer Detection and Classification Using ML	ISIC 2019 (reduced to 800 images)	Multi-class SVM	**96.25%**	Effective preprocessing (Dull Razor, filtering), k-means segmentation, and ABCD + GLCM-based feature extraction improved classification.	Dataset heavily reduced, which may affect generalization; deep learning not applied.
Fakoor et al. (2013)	Deep Learning for Cancer Diagnosis Using Gene Expression	Multiple gene expression datasets (varied cancer types)	PCA + Sparse Autoencoder + Softmax Classifier	Up to **99%**	Deep learning improved performance on high-dimensional gene expression data, enabling scalable and generalized diagnosis.	Relies on compatible microarray platforms, limited interpretability, computationally intensive.
Wasudeo Rahane et al. (2018)	Lung Cancer Detection via Image Processing & ML	CT Scans + Blood Data	SVM	Not explicitly stated	Web-based tool with image preprocessing, feature extraction (Area, Perimeter), and SVM classification reduced diagnosis time.	No accuracy metric provided; offline access a limitation; no external validation.
Khushboo Munir et al. (2019)	Deep Learning Bibliographic Review for Cancer Diagnosis	Multiple (Lung, Breast, Brain, Prostate, Skin)	CNN, GAN, Autoencoders, RNN, LSTM	CNN: **Up to 98%** in melanoma	Deep learning models outperform traditional ML in automation, accuracy, and feature extraction; CNNs most common for imaging.	Large datasets required; high computational demand; challenges in clinical integration.
Kumar Shubham & Dr. R. Kamalraj (2022)	Breast Cancer Detection Using ML Algorithms	WBCD (699 records: 450 benign, 249 malignant)	KNN, SVM, Decision Tree	SVM: **91%**	SVM outperformed other algorithms; ML models achieved higher accuracy than typical physician diagnosis (79%).	No deep learning; modest dataset; generalizability not tested.

TABLE-3

Author(s) & Year	Title / Topic	Dataset & Data Type	Algorithm / Model	Key Findings / Accuracy	Limitations	Result / Impact
Kwang-Hyun Uhm et al. (2021)	Deep Learning for End-to-End Kidney Cancer Diagnosis on Multi-phase Abdominal CT	308 nephrectomy patients' multi-phase CT scans; internal and external test sets	3D U-Net segmentation + Spatial Transformer + ResNet-101 classification	Internal test: AUC 0.889, accuracy 72%; External: AUC 0.855, accuracy 64%; better than radiologists	Single hospital data; external dataset missing some subtypes; only 5 tumor subtypes supported	Automated kidney cancer subtype classification outperforming radiologists; high Dice scores; scalable clinical potential
Ho Sun Shon et al. (2020) Data	Cost-Sensitive Hybrid Deep Learning for Kidney Cancer Classification	1,157 patients' gene expression + clinical data from TCGA	Deep Autoencoder (DAE) + Neural Network classifier with cost-sensitive loss	Sample type prediction accuracy 100%; primary diagnosis 96.98%; tumor stage 56.7%; vital status 76.7%	Black-box model; limited interpretability; could improve with other classifiers	Improved prognosis predictions using integrated genomic deep features; valuable for personalized treatment
Dalia Alzu'bi et al. (2022)	Kidney Tumor Detection and Classification with New CT Dataset	8,400 CT images from 120 patients	CNN-6, ResNet50, VGG16 for detection; CNN-4 for classification	Detection: ResNet50 best (97.47%); classification CNN-4 (92%)	Single center dataset; VGG16 underperformed ; no multimodal imaging	High-accuracy detection/classification ; dataset publicly released to boost research
Francisco Azuaje et al. (2019)	Integrating Histopathology Imaging and Proteomics in Kidney Cancer	CPTAC cohort; histology slides and proteomic profiles	Random Forest (proteomics); VGG16-based CNN (imaging)	Proteomics RF: 98% accuracy; imaging CNN: 95% accuracy; strong biological correlations	Single cohort; small matched data; downsampled histology	Integrative ML links imaging and molecular data; improves understanding and diagnosis
Usha M G et al. (2024)	Kidney Tumor Detection Using MLflow, DVC and Deep Learning	4,583 CT images from Kaggle (tumor vs normal)	Fine-tuned VGG16 CNN with MLflow for tracking, DVC for data versioning	Training accuracy 96%; validation accuracy 94% (binary classification)	No comparison with other models; only binary classification; limited clinical complexity	Reproducible, scalable pipeline for kidney tumor detection; real-time cloud deployment
Ali Muhamed Ali et al. (2018)	ML Classification of Kidney Cancer Subtypes Using miRNA Data	miRNA expression data (1881 samples, 35 key miRNAs selected)	Neighborhood Component Analysis (NCA) + LSTM neural network	Accuracy 95.4% (35 miRNAs); 97.2% (full set with augmentation)	Needs wet-lab and clinical validation	Demonstrates miRNA biomarkers for subtype classification; reduces computational complexity
Liu et al. (2022)	Benign/Malignant Spinal Tumor Diagnosis Using Deep Learning + Weighted Fusion Framework	MRI images + patient age data	Faster R-CNN for detection; ResNeXt101 for classification; age-statistics module	Accuracy 82.1% with imaging + age; outperforms doctors (75%)	Retrospective single center; false positives in detection	AI + clinical metadata fusion improves diagnostic accuracy beyond human experts

Author(s) & Year	Title / Topic	Dataset & Data Type	Algorithm / Model	Key Findings / Accuracy	Limitations	Result / Impact
Rakhi Issrani et al. (2025)	AI in Oral Cancer: Diagnostics, Genetics, Precision Medicine (Review)	Various datasets including histopathology images and genetic data	CNNs, AlexNet, ResNet-101, DeepSurv, SVM, ANFIS, Logistic Regression	CNN models reach 95–98% accuracy; ML models predict metastasis and recurrence well	Black-box nature; data diversity and integration challenges	AI advances early detection, prognosis, precision medicine in oral cancer

TABLE-4

Author and Year	Title / Topic	Finding	Algorithm(s) Used	Accuracy / Performance	Limitation	Result
Dhirendra Prasad Yadav & Sandeep Rathor (2020)	Bone Fracture Detection and Classification Using Deep Learning	CNN with data augmentation increased dataset; achieved higher accuracy than SVM and GLCM	Deep CNN, Adam & Softmax optimizers	Up to 95.67% on fractures, 92.44% overall (5-fold CV)	Small and synthetic dataset; may affect generalizability	CNN model effectively classifies fractures, promising for real diagnostics with more validation needed.
Deepshikha Shrivastava et al. (2020)	Bone Cancer Detection Using Machine Learning Techniques	ML effective in detection and classification; Random Forest and ANN performed well	Decision Trees, SVM, Random Forest, Genetic Algorithms, PSO, ABC, ANN	High but varied; exact not uniform	Large annotated data needed, high computation, lack of standard evaluation	ML shows promise for bone cancer diagnosis, needs further clinical validation, esp. in limited-resource settings.
Wilson Ong et al. (2024)	AI and Deep Learning in CT Spine Imaging for Oncology	AI tools match/outperform radiologists in tumor detection, classification, prognostication	CNN, ResNet-50, U-Net, R-CNN, Radiomics	Sensitivity 66–98%, AUC up to 0.990, accuracy 79–99%	Small sample sizes, data heterogeneity, lack of multi-center validation	AI significantly improves spinal cancer imaging analysis but requires more validation and workflow integration.
Yukihiro Nomura et al. (2023)	CAD for Screening Lower Extremity Lymphedema via CT	ResNet-34 on fat-enhanced CT images had best diagnostic accuracy	ResNet-18, ResNet-34, ResNet-50 (Deep CNN)	AUC 0.967, Accuracy 92.9%, Sensitivity 0.886, Specificity 0.971	Single-center data, female patients only, limited cancer types	Promising CAD tool for early LEL detection, potential for non-invasive screening with further dataset diversity needed.
Kwang-Hyun Uhm et al. (2021)	End-to-End Kidney Cancer Diagnosis on Multi-phase CT	Deep learning outperformed radiologists in subtype classification	3D U-Net, 3D spatial transformer, ResNet-101	Accuracy 0.72 internal, 0.64 external; AUC 0.889 internal, 0.855 external	Single-center training, no rare subtype classification	Strong diagnostic aid with consistent tumor classification; needs rare subtype inclusion and wider validation.

Da-Chuan Cheng et al. (2021)	Bone Metastasis Detection in Chest & Pelvis from Bone Scan	Two networks (pelvis NN, chest NN) detect metastasis well despite small dataset	ResNet-101, YOLO v3, Faster R-CNN	Sensitivity 0.87 (pelvis), 0.82 (chest); specificity 0.81; precision 0.70	Small dataset, limited hardware for deep models	Effective early metastasis detection tool assisting physicians, with improved clinical decision support potential.
Maha Gharaibeh et al. (2022)	Review: ML & DL for Early Kidney Tumor Diagnosis	CNNs like ResNet50, VGG16, U-Net highly accurate but limited by dataset size and generalization	CNN, U-Net, V-Net, SVM, RF, ANN, XGBoost	Up to 97.3% accuracy, AUC > 90%	Small, single-institution datasets, manual segmentations	DL outperforms traditional ML; future focus on larger datasets, automation, and multi-modal imaging needed.
Basem S. Abunasser et al. (2023)	CNN for Breast Cancer Detection & Classification	BCCNN model outperformed pre-trained CNNs across multiple histopathological classes	Custom CNN (BCCNN), ResNet50, VGG16, Xception, InceptionV3, MobileNet	Test accuracy 97.8%, F1-score 98.28%, precision 98.39%, recall 98.3%	Need further clinical validation with hospital data	Deep learning models with data augmentation significantly improve breast cancer detection accuracy.
M. Tahmooresi et al. (2018)	Early Detection of Breast Cancer Using Machine Learning	Hybrid model combining SVM, ANN, KNN, DT improved early detection; SVM best performer	SVM, ANN, KNN, Decision Tree, AdaBoost, Naive Bayes	Up to 99.8% (SVM with optimization)	Data noise sensitivity, dataset imbalance	Combining multiple ML techniques and features improves detection reliability, supporting personalized diagnostics.

3. RESEARCH GAP

i. **Insufficient Real-World Testing:** Models show high accuracy in lab settings but lack clinical trials or hospital-level deployment.

ii. **Over-reliance on CNN Models:** There is limited exploration of newer architectures like Vision Transformers or hybrid ensemble methods.

iii. **Lack of Cross-Modality Studies:** Few papers integrate multiple imaging types (e.g., CT + MRI) for more accurate diagnosis.

iv. **Missing Explainability Tools:** Many AI systems lack explainable AI (XAI) integration, making medical decisions harder to trust.

v. **Neglect of Rare Cancers:** Focus remains on common cancers (breast, lung); rare or aggressive cancers are under-researched.

vi. **Low Focus on Clinical Workflow Integration:** Very few models are tested for compatibility with existing hospital systems and medical practices.

vii. **Inadequate Validation Across Institutions:** Cross-institutional and multi-center validations are rarely conducted.

viii. **No Standardized Evaluation Metrics:** Different studies use varied metrics, making fair comparison of model performance difficult.

ix. **Data Privacy and Ethical Concerns Ignored:** Most papers do not address patient data protection, regulatory compliance, or ethical usage.

4. CONCLUSION

AI and ML are revolutionizing disease diagnosis through medical imaging. Techniques like CNN, ResNet, and hybrid models show high accuracy (90–97%). AI systems outperform traditional methods like SVM and decision trees. Most models excel in detecting bone cancer, breast cancer, and kidney tumors. Data augmentation and deep learning improve diagnostic performance. However, limited datasets and clinical testing remain major challenges. Lack of real-world validation reduces model generalizability. Multi-center studies and diverse datasets are urgently needed. Clinical integration requires collaboration among AI experts and doctors.AI has strong potential, but responsible deployment is essential. However, several limitations persist across studies, including small and non-diverse datasets, lack of multi-center validation, limited real-world clinical testing, and reliance on manually annotated or pre-selected data. These issues affect the generalizability and practical adoption of AI systems in hospitals.

5. FUTURE WORK

i. Incorporate larger and more diverse datasets to improve model generalization across populations.
ii. Develop explainable AI (XAI) techniques to enhance model interpretability for clinical use.
iii. Integrate multi-modal data (e.g., imaging, genomics, and electronic health records) for holistic diagnosis.
iv. Improve model performance using advanced deep learning architecture like transformers and EfficientNet variants.
v. Implement real-time cancer detection systems for use in clinical settings.
vi. Explore unsupervised and semi-supervised learning to reduce reliance on labeled data. 7-Collaborate with healthcare professionals for model validation and real-world testing.
vii. Study the integration of ML systems with IoT and wearable devices for continuous cancer monitoring.
viii. Strengthen data privacy and security in ML-based diagnostic systems.
ix. Design personalized treatment recommendation systems using predictive analytics.

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