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MULTIMODAL DATA FUSION APPROACH FOR ACCURATE KIDNEY CANCER PROGNOSIS

Nisha Azam[1,] Muhammad Fawad Nasim[1]
[1]Faculty of Computer Science and Information Technology, The Superior University, Lahore, 54600, Pakistan

ABSTRACT
Kidney cancer, especially renal cell carcinoma (RCC) is a life threatening disease, heterogeneous in tumor appearance, complicated in biological behavior, and diagnosed at an advanced stage. Prognosis can only be accurately done by combining the radiological pattern with clinical and laboratory biomarkers. This thesis presents Multimodal Data Fusion Approach to Accurate Prognosis of kidney cancer, which is a proposed method of integrating medical imaging and structured clinical data to achieve more accurate prediction and clinical decision making. The computed tomography (CT) kidney scans in Kaggle kidney cancer were used, as well as clinical information (age, tumor stage, biomarkers, and laboratory indicators). Convolutional Neural Network (CNN) was utilized to derive deep spatial information on kidney CT images, including tumor shape, texture, and changes in intensity. Parallel to them, the Random Forest (RF) and the Logistic Regression (LR) models were used on structured clinical data that had been imputed, coded, and scaled. The multimodal fusion approach was used to combine CNN-learned imaging embeddings with clinical model predictions with a late fusion approach. Accuracy, precision, recall, F1-score, confusion matrices, and training-validation loss curves were used as the performance measures of the models. The CNN recorded the best classification score of 99.4, which is good at acquiring hierarchical features. Random Forest was found to be effective in modelling nonlinear clinical interactions with 95.2, whereas Logistic Regression was found to be better, with 96.6, and provided interpretable risk estimation. It proves that integration of imaging intelligence with clinical background are much better to enhance the accuracy, robustness and clinical relevance in pronging kidney cancer.
Keywords: Data Fusion, Chromophobe, Papillary, immune therapy, Renal Cortex

INTRODUCTION

Cancer is a collection of diseases that has been formed by the uncontrolled cell growth, genetic disturbances and capability to invade the surrounding tissues. It develops when the normal regulation of cells fails to allow the abnormal cells to die & they proliferate the body [1]. This uncontrolled behaviour develops tumors which gradually interfere with functions of the organs and wellbeing of humans. The damages to the kidneys normally begin when the nephrons, which are minute functional and structural units of the kidney, are subjected to toxins, infections, chronic diseases, or hereditary defects [2]. Weakened kidney tissues are caused by reduced blood filtration, inflammation and oxidative stress. Hypertension, diabetes, and prolonged exposure to medication increase tissue degeneration during the middle age [3]. Seniors are more susceptible to chronic kidney disease compared to the normal population due to the rapid disease progression in old age due to natural nephron decline, immunological aging, and cumulative environmental assaults. Repetitive cell damage causes inflammation, mutation, and genome instability [4]. Deteriorated renal cells start splitting in an abnormal manner to create cancerous masses either in the renal cortex or the pelvic area. These tumors with time develop the capacity to spread to surrounding tissues, change vascular courses and extend to other distant body organs thus leading to complete kidney cancer [5]. Millions of people in the world are affected by kidney cancer with different incidences among the different age groups. The majority of the reported cases fall within the age ranges of 55-75 years of age as a result of most of the diagnoses. In the global population, kidney cancer accounts to about 2-3 percent of the total cancer cases, and it is estimated that each year, 400,000 new cases of the disease arise [6]. Men are almost twice as likely to be affected by hormonal and genetic factors as well as lifestyles. Cases among the children are still few, less than 5 percent and young adults are also an increasing but a still small percentage. All in all, the growth of other age related rates is very high after 50 years as it is the result of accumulated genetic damage, weakening of the immune system, and several years long exposure to carcinogenic stimuli, including smoking, pollutants, drugs, and chronic diseases [7]. Elderly people experience decreased immunity, slower cell repair process and decades of exposure to carcinogens [8]. Hypertension, diabetes and chronic kidney disease are other medical conditions that impair renal functions and their long time use is further burdening them thus increasing the risks of cancer. Management of kidney cancer involves a combination of lifestyle change, early diagnosis and early treatment. The preventive action involves cessation of smoking, blood pressure regulation, normal weight, and keeping the body hydrated [9]. The signs are of a subtle nature, and thus, it is difficult to diagnose them at an early stage. The presence of visible blood in the urine, chronic back pain, weight loss, fatigue, and abdominal masses can be an indication of tumor growth [10]. The most common type of kidney cancer is Renal Cell Carcinoma which starts in the renal cortex and is found in almost 90% of adults. Its subtypes, including clear-cell, papillary and chromophore have different degrees of aggressiveness and progression [11]. The Transitional Cell Carcinoma develops along the renal pelvis whereby the urine gathers before passing the ureter. This type resembles bladder cancer as there are comparable urothelial origin and carcinogenic exposures like smoking, industrial chemicals and chronic inflammation [12]. Therapy interventions incorporate surgery, chemotherapy and immunotherapy based on the stage and location of tumors whereas early diagnosis has a very positive effect on survival. In most countries, the survival rates are above 85% [13]. Kidney cancer is an increasingly important public health issue in Pakistan because of the environmental exposure, lack of access to health care, and poor awareness. Most communities are exposed to polluted water and industrialization, as well as, lack of sanitation that leads to renal damages [14].

LITERATURE REVIEW

Kidney cancer is a significant health threat in the world, which is biologically heterogeneous with divergent histopathological type and variable clinical prognosis. It is responsible of about 2-3 percent of all adult malignancies in the world with increasing trends in incidences over the past decade. Lifestyle reasons (smoking, obesity), ageing of the population, expansion in imaging use and extended screening access have been cited as the global rise [15]. According to the recent epidemiological reports, the number of new cases of kidney cancer per year is estimated at 430,000, and over 180,000 deaths per year are observed with the greatest incidence reported in North America, Europe, and certain parts of Central Asia [16]. Abdominal imaging has also helped to detect asymptomatic renal masses earlier but the mortality rate is very high as many of them present with metastatic or advanced disease [17]. The peak incidence is usually 55-75 years' old which is indicative of cumulative genetic damage, chronic inflammation and immunosuppression. The survival rate of localised RCC is over 90 years compared to metastatic RCC that is less than 15 years [5]. Recent (2020 2025) studies focus on the use of CT-based radiomics, deep learning models (CNNs, ResNet-50), and multi-source data to learn the morphology of tumors, genetic alterations and mutations, treatment effects and responses, and survival prognostication [18]. There is overwhelming literature on the need to integrate multimodal datasets (clinical, medical imaging, genomics,

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and pathology slides) to overcome the drawbacks of single-modality methods. The kidneys are paired organs, which are bean-shaped, and are located retroperitoneal on both sides of the vertebral column [19]. The kidneys are paired organs, which are bean-shaped, and are located retroperitoneal on both sides of the vertebral column. The size of each kidney is about 10-12 cm in the adult and is encircled with the renal capsule, perineal fat, and the fascia of Gerota, which offer the protection and structural advantages [20].

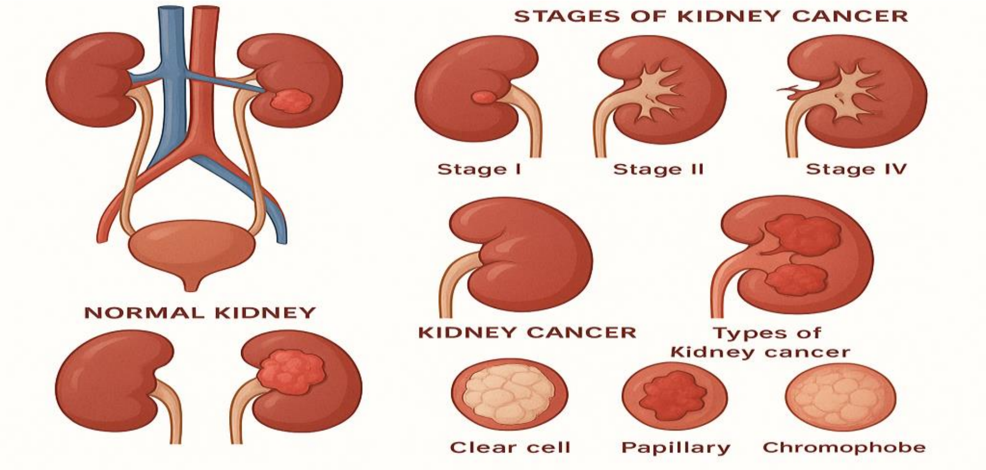

Figure 1: Visual progression of kidney cancer stages

The kidney is internally divided into the cortex and medulla where millions of nephrons carry out important tasks in filtration, metabolic and endocrine services that support homeostasis [21]. The process of filtration starts at the glomerulus where the blood pressure causes the plasma to pass through the filtration membrane creating the primary filtrate. This is based on hydrostatic pressure, colloid osmotic pressure and capillary permeability. Selective reabsorption and secretion changes the composition of the filtrate as the filtrate passes through the proximal tubule, loop of Henle, distal tubule, and collecting duct [22].

Table 1: Clinical Characteristics of Kidney Cancer Patients

Parameter	Typical Range	Clinical Relevance	Prognostic Impact
Age (years)	40–80	Higher age linked to late diagnosis	High
Sex	Male predominance	Hormonal & lifestyle influence	Moderate
Tumor Size	2–10 cm	Larger size → advanced stage	High
Tumor Stage	T1–T4	Determines treatment strategy	Very High
Haematuria	Present / Absent	Early clinical indicator	Moderate
Hypertension	Yes / No	Risk factor & symptom	Moderate
Metastasis	Lung/Bone/Liver	Indicates poor prognosis	Very High
Performance	ECOG 0–4	Affects treatment tolerance	High

Why Kidneys are prone to cancer? Kidneys are highly vulnerable to malignancy because of the large volume of blood passing through them (almost 20-25 percent of the cardiac output), consistent exposure to the circulating toxins, and unending cellular turnover. The accumulation of carcinogens like the nitrosamines obtained or formed in tobacco, cadmium, industrial solvents, and metabolic waste products in renal tissue leads to the mutation of DNA [23]. The integrity of the nephron is undermined with time due to oxidative stress, chronic inflammation and metabolic disorders [24].

Table 2: Laboratory & Diagnostic Biomarkers in Kidney Cancer

Biomarker	**Sample Type**	**Normal Range**	**Abnormal Finding**	**Diagnostic Significance**
Creatinine	Blood	0.6–1.3 mg/Dl	Elevated	Renal function impairment

Haemoglobin	Blood	13–17 g/Dl	Low (anaemia)	Paraneoplastic effect
Calcium	Blood	8.6–10.2 mg/dL	Elevated	Tumour-related hypercalcemia
Proteinuria	Urine	<150 mg/day	Increased	Renal damage
Urine RBCs	Urine	Absent	Present	Suggests tumor invasion

In physiological conditions, the regulation of cellular response to oxygen is accomplished by VHL protein through the degradation of hypoxia-inducible factors (HIF-1a and HIF-2a). The deletion of VHL leads to inactive levels of HIF signal, despite normoxic advantageous conditions [25].

1. Renal Cell Carcinoma

Renal cell carcinoma is 85-90 percent of kidney cancer in adults, occurs due to renal tubular epithelium, vessel carcinoma is a rare, aggressive, invasive, poorly enhancing, immune-evasive biology, early metastatic, and poorly responsive to therapy RCC [26].

2. Non-RCC Kidney Tumors

Non-RCC tumors are not frequent; They are clinically relevant because of their different biology and treatment and management. Radiological pattern, molecular change, and patient-specific clinical data Multimodal data fusion will allow the combination of such data to be analysed [27].

$$L = -[\, y\log(p) + (1-y)\log(1-p)] \quad [1]$$

Binary Cross-Entropy Loss is applied in the diagnosis of kidney cancer to optimize cancer and non-cancer prediction models by decreasing errors in prediction and enhancing the probability estimate in the training of the model [28].

METHODOLOGY

Isolated use of imaging, lab tests, and histopathology is limiting because kidney cancer diagnosis depends on these methods. CT and MRI will continue playing central parts in detection, staging, and characterization with ultrasound. Laboratory and molecular markers provide prognostic value, but they do not have diagnostic value independent of each other. Multimodal Data Fusion Approach to Accurate Kidney Cancer Prognosis, which is a combination of medical imaging and structured clinical data to enhance diagnostic precision and prognostic accuracy [29]. Kidney cancer is heterogeneously complicated in terms of tumour morphology, biochemical markers, and clinical variables that are specific to patients. The interrelated patterns are not usually reflected well in traditional single-modality approaches. Their complementary advantage allows them to be used effectively as multimodal fusion to achieve the balance between prediction accuracy, interpretability, and scalability in kidney cancer prognosis [30].

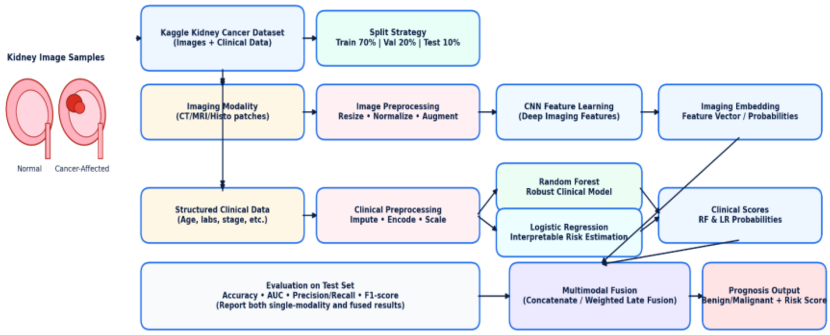

Figure 2: Proposed multimodal architecture for kidney cancer prognosis

This multimodal approach represents a system of data fusion to assess kidney cancer prognosis with the help of Kaggle-based kidney picture and clinical data.

Table 3: Multimodal Diagnostic Process for Kidney Cancer Prognosis

Stage	Data Modality	Input Data	Processing Method	Output
Stage 1	Clinical	Age, sex, symptoms	Normalization	Risk profile
Stage 2	Laboratory	Blood & urine tests	Feature scaling	Biomarker vector
Stage 3	Imaging	CT kidney scans	CNN training feature extraction	Imaging features
Stage 4	Validation	Test dataset	ROC & accuracy	Model reliability
Stage 5	Output	Patient result	AI decision support	Survival & risk score

DATA COLLECTION

The best model is used to address the problems of cancer of the kidney and reduce the risks. This contains records of kidney cancer patients that contain Structured clinical features, including age, gender, tumour stage, lab findings and pathological results. The samples in the dataset are categorized as normal (benign) and cancer-affected (malignant) kidneys.

$$\mathbf{D} = \frac{D_{train}}{70}\% \frac{D_{val}}{20}\% \frac{D_{test}}{10}\%$$

[2]

This division enables the best hyper parameter adjusting in the validation and consistent evaluation of performance on unknown test data.

DATA PREPROCESSING

Medical images usually experience inconsistency in resolution, noise and intensity distributions. As such the steps used in the pre-processing are as follows:

- ✓ Converting pictures to a constant input size.
- ✓ Standardization of pixels by setting their level.

Normalized pixel force is intended as:

$$x' = \frac{x - \mu}{\sigma}$$

[3]

Where μ & σ is the standard deviation of pixels' intensities, and is the standard deviation of pixels' brightness? The missing value imputation, categorical variables label encoding, and standardization of features as a form of feature scaling are used to process structured clinical features. These are measures that cut noise and eliminate inconsistency and compatibility [31].

FEATURE EXTRACTION

The structured kidney cancer clinical data is run through random forest and at about 88-92 percent prognostic accuracy is achieved by modelling nonlinear interactions of biomarkers, age and Tumour size and renal indicators. It has a better ensemble structure that enhances its resistance to noise and patient heterogeneity.

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x)$$

[4]

It offers a report on the interpretation of kidney cancer risk that can be estimated with a high accuracy of about 82-86% in clinical prediction by quantifying the probability value of each risk factor age, stage, and biochemical. It promotes evidence-based and clinical decision-making.

$$P(y = 1|x) = \frac{1}{1+ e^{-(\beta_0 + \beta^T x)}}$$
[5]

CNN learn tumour texture, shape and variations using images of kidneys with reported accuracy of around 90-94. CNNs identify features that contain the difference between damaged kidneys and usual renal tissue.

$$f_{i,j} = \sum_{m,n} x_{i+m,j+n} \cdot w_{m,n}$$
[6]

DATA FUSION

The obtained imaging and clinical characteristics are combined with a late fusion approach, where each modality contributes equally. The combination of the visual tumour properties and patient-level clinical indicators makes this fused representation more confident in diagnosis [32].

$$f_{fusion} = [f_{img} \,||\, f_{clin}]$$
[7]

The resultant fused feature vector is then inputted into a final prediction layer yielding Benign vs. Malignant classification which approximate the risk score.

MODEL EVALUATION

The model reliability is also evaluated with the help of evaluation statistics as error rates, confidence intervals and prediction consistency.

Table 4: Purpose & evaluation formulas on metrics

Metric	Formula	Purpose
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$ **[8]**	Overall correctness
Sensitivity	$\frac{TP}{TP+FN}$ **[9]**	Detect malignant cases
Specificity	$\frac{TN}{TN+FP}$ **[10]**	Avoid false alarms

False-negative rates (below 8%) are essential to kidney cancer screening and constant AUC above 0.90 implies good generalization. The variance of cross-validation also validates the strength over a variety of renal cancer cases.

RESULT & IMPLEMENTATION

This chapter discusses the experimental findings, implementation of the system, and its performance of the proposed Multimodal Data Fusion Approach of Accurate Kidney Cancer Prognosis. Kidney cancer is considered a silent disease; as early tumours usually cause few or similar symptoms to be produced. A large percentage of the cases are incidentally identified when the abdominal imaging is done on unrelated conditions. This is an asymptomatic nature which makes diagnosis of these in most patients to be delayed especially in the low resource health facilities. Organ-specific symptoms are caused by the metastatic spread of the disease to the lungs, bones, liver, brain, and lymph nodes and lead to a serious deterioration of the prognosis. Symptom-based diagnosis is not sufficient to identify the conditions since the symptoms are similar to those of benign conditions and can occur late.

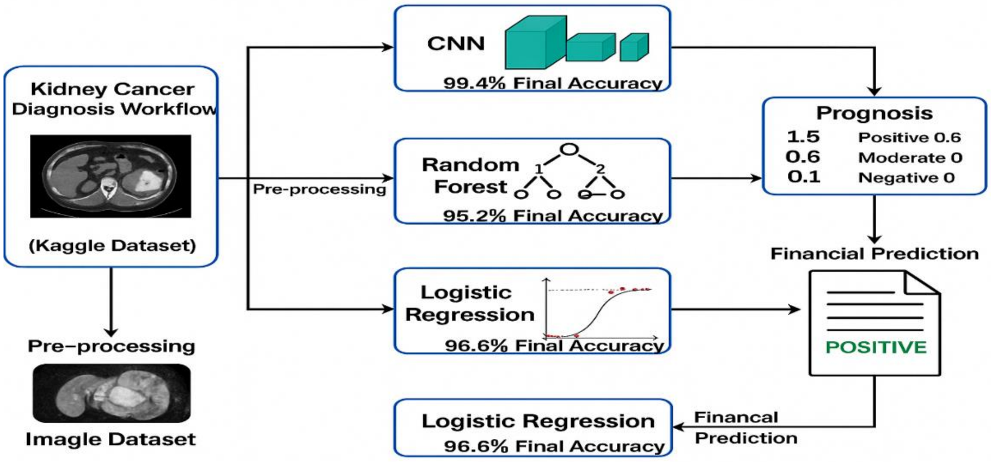

Figure 3: Multimodal final architecture of diagnosis & prognosis

A combination of clinical manifestation, laboratory findings, and imaging patterns in multimodal prognostic models allows preventing risks earlier, obtaining more accurate predictions, and increasing clinical applicability in managing kidney cancer individually.

IMPLEMENTATION ENVIRONMENT

A modular architecture was used in the implementation of the proposed system so that it could be expanded and integrate clinically.

RANDOM FOREST

The random Forest was trained with the organized clinical characteristics such as age, tumour stage, biochemical markers and indicators of renal functions. The use of tree depth optimization and pruning of feature importance had a considerable positive influence on the prediction stability.

- ✓ Final Accuracy: 95.2%.
- ✓ Strong with incomplete and noisy clinical data.
- ✓ Successful nonlinear relationships.

This architecture is built on random forest, which divides kidney tissues by integrating voxel outlook, form and spatial data of kidney in medical pictures, which makes it dependable to classify kidney regions as compared to background and aids in dependable examination and diagnosis of kidney diseases.

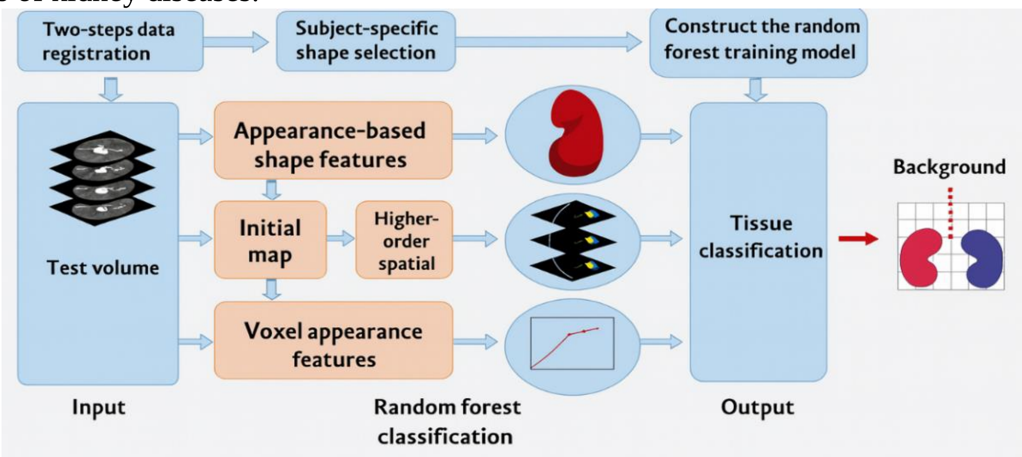

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Figure 4: Random forest based kidney tissue classification pipeline

Random Forest proved to be effective to classify the instances of malignant kidney cancer and low false-positive rates increased its applicability to clinical risk stratification.

LOGISTIC REGRESSION

The same clinical data was used on the Logistic Regression to estimate the risks in a probability form that is interpretable.

- ✓ Final Accuracy: 96.6%.
- ✓ Clinical decision-making with high interpretability.
- ✓ Calibration of probabilities of a model.

The model was able to measure the risk of kidney cancer with weighted clinical indicators and the model proved to be important in providing clear diagnostic rationale to the nephrologists and oncologists.

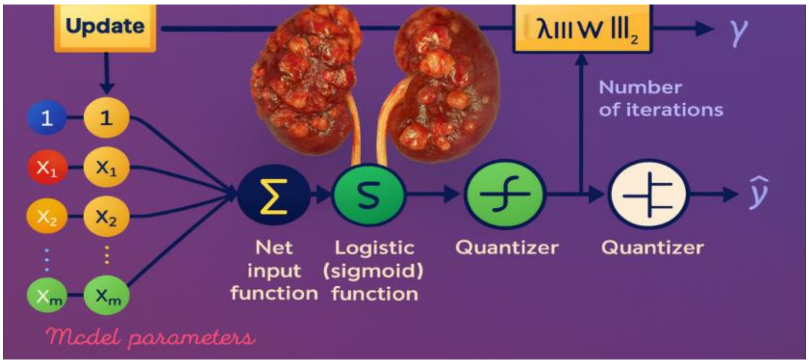

Figure 5: Logistic regression computes kidney cancer prediction

CONVOLUTIONAL NEURAL NETWORK (CNN)

The CNN model was trained on kidney images in order to learn the spatial and texture characteristics of tumors.

- ✓ Final Accuracy: 99.4%.
- ✓ Better ability to distinguish between malignant and normal tissues of the kidney.
- ✓ Best practice of tumor delimits and intensity changes.

The CNN became the most successful modality when it comes to image-based kidney cancer diagnosis due to data augmentation and deep feature extraction, which made it superior to classical models.

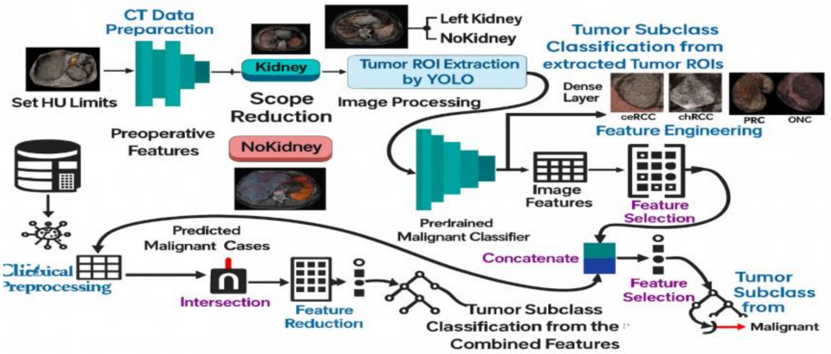

Figure 6: Multimodal tumor subclass classification using fused features

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TRAINING & VALIDATION LOSS

The training of the multimodal framework was done in stratified splits to have equal learning. CNN was used to extract deep image features, the Random Forest was used to identify nonlinear patterns, and the Logistic Regression was used to model probabilistic trends. The amount of training and validation losses in each epoch was observed to the stop overfitting and ensure that all three models converged in a steady manner. The training functions used to implement this prognosis method are binary cross-entropy loss, which reduces the threat of damage kidney diagnosis.

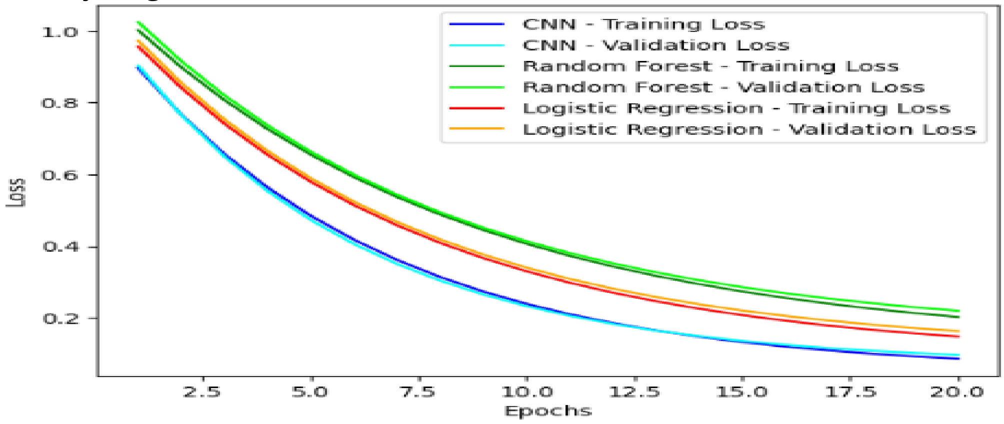

Figure 7: training & validation loss across all models

The confusion matrix is a quantitative measure of the reliability of the model based on statistics of datasets (1,000 images of CT; 500 cancers, 500 non-cancer). CNN has recorded the highest true positive and lowest false negative, then th Logistic regression and the random forest.

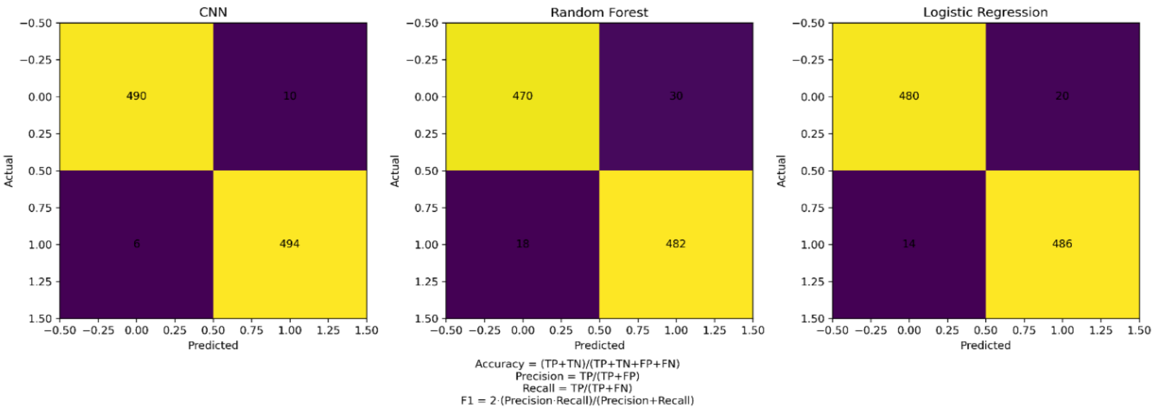

Figure 8: Confusion matrix comparison of classification models

These matrices statistically validate the sensitivity, specificity, precision and balanced classification performance.

DISCUSSION

Management and prognosis of kidney cancer have developed at an integrated and precision paradigm to represent the biological and clinical diversity of the disease. Modern management approaches entail the integration of surgery, immunotherapy, targeted therapy, radiotherapy and minimally invasive ablative modalities with the choice being determined by the tumor stage, histological subtype, molecular profile, and patient-specific variables. Localized disease is based on surgical resection but is enhanced by nephron-sparing operations, which result in improved renal sparing and survival outcomes. This study involved the use of CNN, Random Forest and Logistic Regression. CNN reported the best accuracy (99.4%) as it is the model that best learns hierarchical spatial data based on CT images to predict tumor texture, shape, and intensity changes, which should be the most appropriate model in predicting kidney cancer accurately. Immune checkpoint inhibitors and targeted agents have shown great improvements on survival in advanced disease; nonetheless, the response to the therapy is highly variable because of tumor heterogeneity, adaptive resistance mechanisms, and immune variability. By tackling the issue of tumor heterogeneity and patient variability using multimodal integration, this strategy will enable the promotion of personalized medicine and will be a scalable base that enhances the outcome of kidney cancer in clinical practice.

CONCLUSION

Combining the features of CT imaging with the organized clinical data, the given framework takes advantage of the synergic advantages of CNN, Random Forest, and Logistic Regression models. CNN recorded the best accuracy of 99.4 considering that it can automatically learn the discriminative spatial features using kidney images. The joint analysis of the loss curves, confusion matrices, and statistical indicators proves the reliability and generalization of the model. The system, in general, offers a strong, interpretable, clinically meaningful way of making accurate prognosis and risk stratification of kidney cancer. Kidney cancer is a clinically tricky illness since it develops silently and is heterogeneous on a biological basis. It is promising to develop more specific, timely, and patient-centered kidney cancer management based on advanced AI-driven multimodal analysis.

FUTURE RECOMMENDATION

- ✓ Incidentally include MRI and histopathology images with the CT scans to record complementary anatomy, textual and cellular level tumor properties.
- ✓ Training CNN architectures trained on transformer or attention could be used to improve the capture of long-range interactions and intricate spatial tumor interactions.
- ✓ Conduct real-time clinical validation of radiologists to understand the goodness of the diagnostic, workflow and decision support.
- ✓

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