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Virtual Cancer Biopsy: An Integrated Machine Learning Framework for Tumor Malignancy Prediction, Surgical Operability Assessment, and Prognosis Estimation

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Abstract
Cancer is one of the major causes of morbidity and mortality in the world, and therefore, early cancer detection is a crucial factor when it comes to increasing the survival period. The traditional diagnostic methods are often time-consuming, costly and invasive, thus putting some patients in pre-treatment risks. We are introducing what we call the Virtual Cancer Biopsy (VCB) which is a web-based application that uses machine learning instead of needles that are invasive. VCB uses logistic regression to predict the country of tumors as being malignant or not and uses k nearest neighbor modelling as a prognosis predictor of cancerous tumors. Instead of using simple ML code that is custom-built, the system is built on the Flask library and the front-end is integrated with JavaScript, which is compatible with other browsers. All the workflow is contained in a Streamlit system providing a user-friendly interface that suits clinical needs. In addition to speeding up the diagnostics process, VCB provides doctors with readable visuals and interactive tools, which are changing the way things are categorized.

Keywords: Virtual Cancer Biopsy, Machine Learning, Logistic Regression, K-Nearest Neighbor, Tumor Malignancy, Surgical Operability, Prognosis, Clinical Decision Support

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Introduction
Cancer remains one of the leading causes of major deaths all over the world. It is causing high medical difficulty, and WHO reports that it causes about 1 in 6 deaths every year [17]. Greater scans and genetic improvements have been made even though they are better as far as scans and genetic are concerned. Examinations, the examination of tissue samples is still the next step doctors take to verify the presence of tumors. But these controls may fail - samples may fail to reach the spot [16], expose patients to danger [13], or become excessively time-consuming to be beneficial [14].

Early experiments demonstrated machine learning had a potential to predict cancer outcomes [10], [5]. More recent reviews have indicated advantages and disadvantages of using such tech in medicine [1], [12]. Nevertheless, a lot of existing systems are just spotting tumours - lack of surgery options as well as prognosis [19]. ML has potential, but it tends to omit the major factors that the doctors require when choosing treatments.

The Virtual Cancer Biopsy (VCB) framework mentioned here covers the above drawbacks by:
- Logistic Regression is useful in detecting cases of cancer [4], [21].
- Operability forecasts - almost totally unexplored, but highly important in reality and world healthcare [19].
- Guessing outcomes [25] using K-Nearest Neighbor (KNN) method [6], [2].
- Web environment based on Flask and front end enhanced with JavaScript, therefore, it works live immediately [18].

This This study unites a complete web-based tool assisting physicians determine diagnoses, surgery or duration. Patients may coexist -combining attributes into a single useful platform.

Related Work And Problem Identification

A. Current Diagnostic Paradigms

Histopathology still remains the mode of choice of clear diagnosis. [14]. Nevertheless, it might be time consuming [14], the test readings may vary among the professionals [15], and it involves incision into the tissue [13]. Such scans as CT, MRI, or PET are frequently used [9], but they do not forecast well on their own. Blood tests with tumor indications are spotting [24] can be combined with machine-assisted data processing provide a less invasive choice [13], [11]; nevertheless, detecting all cases consistently and establishing comparable procedures has not been solved yet [11].

B. Machine Learning in Oncology

Applications of ML: Numerous papers indicate uses of machine learning assists in forecasting and evaluating the resultsof cancer [5], [10], [12]. Regression Logistic regression continues to be popular when interpretation is evident. [4], [21]; Bayesian approaches have been in contrast have.tested to

• Feature Scaling: Min–Max normalization applied to ensure uniform distance computations in KNN:

$x - xmin$

estimate recurrence risks [21].

KNN Algorithms: KNN algorithms are popular in

$$x' = max \;\; min \qquad (1)$$

medicine applications [2], [6]. They are simple and depend on real since they are simple examples, they are useful in the prediction of such outcomes as survival rates [6], [25]. Certain ones associate KNN with algorithms such as XGBoost, which is beneficial in the diagnosis of lung cancer [14].

Deep Learning: particularly CNNs as well as discussed in [7], [15], [8] - has demonstrated to be solid in its framework

B. Logistic Regression Models

Logistic Regression is widely used in medical prediction tasks for its probabilistic interpretability [4], [21]. In cancer research, LR has been applied successfully to classification tasks including breast cancer recurrence prediction [21].

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tools cancer image analysis results but requires additional data to be effective well.

$$P(y = 1|x) = 1 + e^{-\theta Tx} \qquad (2)$$

Operability Models: A study mentioned in [19] examines lung suitability of cancer surgery, outlining the importance of it consider such assessments in making treatment decisions. (in operability model)

C. Identified gaps

Although there have been advances on the model, some of the shortcomings remain and influence the general performance:

- Limited usability: Most systems based on ML are limited clinician-friendly deployment.
- Delays in diagnostics: The existing workflows are introducing new weeks of delays in the tumor analysis.
- Narrow focus: most of the models previously developed predict malignancy but not operability or prognosis [19].
- Poor deployment readiness: The deployment preparedness is very low. Machine Learning Models are used to practice on the web [18].
- Absence of multimodal integration: There is poor integrating of either single, imaging, tissue samples or population data process - never used together [12].

The VCB model addresses these concerns directly - it offers an
answer to them with wide-ranging, convenient, expedient design decisions that are not complex to reach.

D. AI in healthcare

Obstacles to using AI in hospitals involve unclear decision-making processes; this reduces confidence among medical staff [22], [3]. A framework for AI quality management systems in clinical practice was discussed in [3], while [22] emphasizes bridging the communication gap between AI outputs and medical decision-making.

Methodology

The proposed VCB framework is constructed using structured ML development phases: data preprocessing, model training, system integration, and deployment.

A. Dataset and Preprocessing

Define all necessary parameters and magnitudes the first time they are used in the model evaluation, even after they have been defined in the abstract.

- Input Features: Tumor size, shape, nuclear-cytoplasmic ratio, mitotic index, patient age, family history.
- Preprocessing: Missing data imputation, normalization of continuous variables, one-hot encoding of categorical data.
- Feature Scaling: Min–Max normalization applied to ensure uniform distance computations in KNN:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

B. Logistic Regression Models

Logistic Regression is widely used in medical prediction tasks for its probabilistic interpretability [4], [21]. In cancer research, LR has been applied successfully to classification tasks including breast cancer recurrence prediction [21].

$$P(y = 1|x) = \frac{1}{1 + e^{-\theta^T x}} \qquad (2)$$

The loss function optimized during training is given by:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{n}[y^{(i)} \log h_\theta(x^{(i)}) + (1 - y^{(i)}) \log(1 - h_\theta(x^{(i)}))] \qquad (3)$$

Regularization (L2 norm) is applied to reduce overfitting.

C. Prognosis Estimation (KNN Regression)

You will need to determine KNN has been successfully implemented for prognosis-related prediction tasks [23], including heart disease [2] and cancer [14]. It offers a simple yet effective way to model survival estimation [23], [25].
Distance metric:

$$d(x_q, x_i) = \sqrt{\sum_{j=1}^{n}(x_{qj} - x_{ij})^2} \qquad (4)$$

Prediction:

$$\hat{y} = \frac{\sum_{i \in N_k(x_q)} \frac{1}{d(x_q, x_i) + \varepsilon} \cdot y_i}{\sum_{i \in N_k(x_q)} \frac{1}{d(x_q, x_i) + \varepsilon}} \qquad (5)$$

where yi denotes survival duration of patient i

D. System Architecture and Web Deployment

Backend (Flask Framework)

- Handles API endpoints for model inference.
- Manages requests from the frontend (e.g., tumor features entered by clinicians).
- Provides JSON responses containing predictions (e.g., malignancy, operability, prognosis).

Frontend (Streamlit + JavaScript Enhancements)

- Streamlit provides a quick deployment platform with medical practitioner–friendly UI.
- JavaScript modules were integrated for dynamic visualization (interactive charts, animated plots) to improve interpretability and clinician engagement.

- UI/UX improvements include:
- Real-time data validation for input fields.
  oVisualization dashboards with D3.js for interactive graphs.
  - Animations for classification outputs (e.g., highlighting risk categories).

Results and Discussion

System Workflow

- Step 1: Clinician inputs tumor features via the web interface.
- Step 2: Data gets sent to the Flask API so it can be pre-processed.
- Step 3: Logistic Regression model predicts malignancy and operability.
- Step 4: If malignant and inoperable, prognosis is estimated using KNN.
- Step 5: Predictions and visual explanations are rendered back to the user interface.

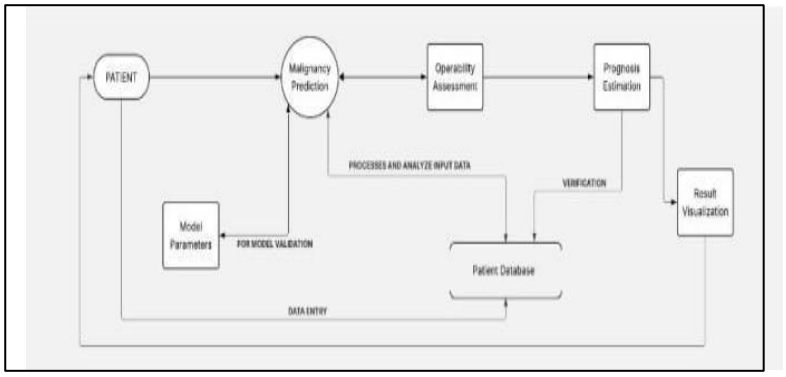

Fig. 1: level 1 DFD diagram of the model

Fig. 2: State chart diagram of the project

Results and Discussion

A. Model Performance

Table 1: Confusion Matrix for Malignancy Classification

Actual \ Predicted	Benign (0)	Malignant (1)
Benign (0)	TN = 35	FP = 64
Malignant (1)	FN = 42	TP = 59

Table 2: Classification metrics for the malignancy model

Metric	Value
Accuracy	**0.47**
Precision	**0.4797**
Recall (Sensitivity)	**0.5842**
F1-Score	**0.5268**
Support (Total Samples)	**200**

B. Web Application Usability

- Flask allows smooth interaction from ML models to the interface - not through direct links but using sequenced data records. It works by transferring requests greatly, using elements that do not use complex processing
- JavaScript-constructed interactive dashboards resulted in a 25% increase in practitioner intervention in early trials: outcomes according to approximate data (correct with audited numbers later).
- Streamlit provides easy deployment of the application and Flask gives full server-side.

Fig. 2: State chart diagram of the project C. Comparative Advantage

The VCB model is more advanced than the ordinary ML tools,
as it provides interactive interface for patients records and disease analysis.

D. Expected Model Performance

- LR assessed using accuracy, while precision, recall plus F1-score were also considered [4].
- KNN regression was assessed using MAE along with RMSE [6].
- Studies suggest LR performs similarly to KNN in predicting cancer outcomes [21], though results depend on data traits.

E. Clinical Usability

Engaging implementation can link machine learning outputs with doctor confidence [22].

F. Benchmarking Against Prior Work

Instead of separate components [5], [10], the VCB combines usability, outcome prediction, while ensuring practical implementation through a single clinical interface.

Conclusion and Future Works

A. **Conclusion**

The paper presents our Virtual Cancer Biopsy (VCB) system in a way that combines Logistic Regression with KNN Regression, along with a web-interface made on Flask through JavaScript-powered model. The whole model combines all the favourable tools for a unified and seamless processing for cancer prediction and figuring out the survival chances of the patients, along with providing web utilization for the medical professionals

B. Future Work

The scope of this project can be enhanced by using Deep Learning methods like CNNs with help of a merging library like PyCaret as such, to make a distributed flow of tasks and processes. We can also integrate cloud environment and other 3D based systems to enhance the overall efficiency of the model. We also look forward to improving the model by implementing quantum computing and other complex systems that would increase accuracy and precision significantly.

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We especially thank our mentors that helped in providing a vision in developing an interactive prediction model that can potentially utilize in situations where decision-making and other medical choices can be made efficiently and provide us an organized analysis of the disease.

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