

AI-Based Uterus Cancer Risk Prediction and Decision Support System Using Machine Learning

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Abstract – Uterine cancer, particularly endometrial cancer, is one of the significant gynecological cancers affecting women globally. Its development is linked to several factors, including demographic characteristics, reproductive history, hormonal changes, metabolic conditions, and lifestyle factors [1][2]. Early identification of individuals who may be at risk can help them receive timely medical attention and improve their awareness of preventive healthcare measures [3]. Recent progress in Artificial Intelligence (AI) and Machine Learning (ML) has made it possible to process multiple patient-related factors and identify patterns associated with cancer risk [4][5]. This paper introduces an AI-Based Uterus Cancer Risk Prediction and Decision Support System that supports the preliminary assessment of uterine cancer risk using relevant patient data. The system combines an AI-driven prediction module with a Flask-based web application to collect patient details, generate a risk prediction, classify the level of risk, and provide suitable recommendations. A database is also incorporated to securely store user information and previous prediction records for future reference. The proposed system provides a simple and accessible platform for preliminary risk assessment and supports users in recognizing potential risk conditions and seeking appropriate medical consultation. The system is intended as a decision-support and awareness tool and does not replace professional clinical diagnosis.

Key Words: Uterine Cancer, Endometrial Cancer, Artificial Intelligence, Machine Learning, Cancer Risk Prediction, Risk Assessment, Decision Support System, Healthcare, Flask.

1.INTRODUCTION

Uterine cancer, with endometrial cancer being one of its major forms, represents an important health concern among women. The likelihood of developing this disease can be influenced by a combination of factors such as age, obesity, diabetes, reproductive characteristics, hormonal exposure, and lifestyle-related conditions [1][2]. Since these factors differ across

individuals and may occur together, evaluating the overall level of risk through manual assessment can be difficult.

Recognizing possible risk at an early stage may encourage individuals to seek medical advice before the condition progresses. Conventional evaluation generally involves reviewing the patient's medical history, conducting clinical examinations, and performing diagnostic investigations when considered necessary [3]. Although these approaches remain important, handling several patient-related factors together can be challenging without computational assistance. A system capable of organizing such information and providing an initial risk assessment can therefore serve as a useful support mechanism.

The increasing use of Artificial Intelligence (AI) and Machine Learning (ML) in healthcare has created opportunities to analyze patient information more efficiently. Machine learning techniques can examine multiple attributes simultaneously and learn relationships between input characteristics and health-related outcomes [4]. Earlier studies have also investigated the application of machine learning to endometrial cancer risk assessment, diagnosis, and clinical decision-support applications, indicating the potential of these techniques in healthcare [5][6].

In this work, an AI-Based Uterus Cancer Risk Prediction and Decision Support System is proposed for preliminary risk assessment. The system allows relevant patient information to be entered through a web-based interface and processes the provided information through an AI-based prediction module. The generated result is subsequently converted into a risk category, and an appropriate recommendation is presented to the user. The application also maintains previous prediction records in a database, allowing earlier assessments to be accessed when required. A Flask-based web framework is used to integrate these functionalities into a single application.

The proposed system is designed primarily for risk awareness and preliminary decision support. It is not intended to provide a clinical diagnosis or replace the judgment of qualified healthcare professionals. By combining patient-data

processing, AI-based prediction, risk categorization, recommendations, and prediction-history management, the system provides an integrated approach for supporting awareness of potential uterine cancer risk and encouraging timely medical consultation when appropriate.

2. PROBLEM STATEMENT

Uterine cancer risk is influenced by multiple patient-related factors, including age, reproductive history, hormonal conditions, obesity, diabetes, and lifestyle characteristics [1][2]. Assessing these factors manually can make preliminary risk evaluation time-consuming and may not provide a consistent assessment when several variables need to be considered together. Although machine learning has shown potential in analyzing clinical and patient-related information for cancer risk prediction [3][4], many existing approaches are developed mainly for research or clinical environments and may not provide a simple, integrated interface for preliminary risk assessment.

Therefore, there is a need for an accessible AI-based system that can collect relevant patient information, analyze the available factors, provide a preliminary uterine cancer risk prediction, and present the outcome in an understandable form. The system should also maintain previous prediction records and provide suitable recommendations based on the identified risk level.

The proposed AI-Based Uterus Cancer Risk Prediction and Decision Support System address this requirement by integrating an AI-based prediction module with a Flask web application and database. The system aims to provide automated preliminary risk assessment while supporting users in understanding their risk level and encouraging appropriate medical consultation. It is designed as a decision-support tool and is not intended to replace professional medical diagnosis.

3. OBJECTIVES

The primary aim of the proposed AI-Based Uterus Cancer Risk Prediction and Decision Support System is to create an accessible platform that can use patient-related information to provide a preliminary indication of uterine cancer risk.

The specific objectives of the proposed system are:

1. **To develop an AI-driven prediction mechanism** that evaluates relevant patient characteristics and provides an initial estimation of uterine cancer risk.
2. **To implement an automated risk-level classification process** that converts the prediction outcome into clearly defined categories that can be easily understood by users.
3. **To design a simple and user-friendly web interface** through which users can provide the required patient information and obtain the corresponding prediction results.
4. **To generate risk-based recommendations** that provide appropriate guidance according to the predicted risk level and encourage medical consultation when necessary.

5. **To maintain a record of previous predictions** using a database, enabling users to access and review their earlier assessment results.
6. **To combine AI-based prediction with web technologies** through a Flask-based application, providing an integrated platform for healthcare-related risk assessment and decision support.
7. **To promote early risk awareness** by providing preliminary information about potential risk and encouraging individuals with concerning results to seek evaluation from qualified healthcare professionals.

4. LITERATURE REVIEW

Artificial Intelligence (AI) and Machine Learning (ML) have become increasingly relevant in healthcare research, particularly in areas involving cancer prediction, diagnosis, and risk evaluation. Conventional assessment of uterine cancer commonly makes use of clinical history, patient characteristics, medical imaging, and laboratory-based investigations. While these methods remain important, the growing volume of healthcare information has created an opportunity to use computational techniques for examining several risk-related factors together [5][6].

Research on endometrial cancer has investigated the use of machine learning models for estimating disease risk from different patient characteristics. Variables associated with demographic background, reproductive history, hormonal factors, metabolic conditions, and lifestyle have been considered in such studies [7][8]. The use of multiple characteristics together can help computational models identify relationships that may not be apparent when individual factors are examined separately.

AI-based techniques have also gained attention in medical image analysis. In particular, deep learning approaches such as Convolutional Neural Networks (CNNs) have been used to learn complex visual patterns and support the classification of medical conditions [9][10]. Within cancer-related applications, image-based models have been explored for identifying abnormal patterns and assisting diagnostic processes. However, effective use of these approaches depends on factors such as the availability of appropriate datasets, suitable preprocessing procedures, and proper model validation.

Clinical decision-support systems represent another area where AI can contribute to healthcare applications. These systems can process healthcare information and present the resulting information in a form that is easier for users or healthcare professionals to interpret during an initial assessment [11]. Incorporating risk categories and recommendation mechanisms can further improve the practical usefulness of such systems by presenting prediction results in a more understandable manner.

Despite the progress in AI-based healthcare applications, several factors can influence the reliability of uterine cancer prediction systems. Variations in datasets, patient groups, input features, model techniques, and evaluation procedures may lead to differences in prediction performance [12]. In addition, an AI-generated prediction should not be treated as a definitive medical diagnosis, since such systems are intended to provide supportive information rather than replace professional clinical assessment.

Considering these existing developments, the proposed work combines patient-data-based risk prediction with risk categorization, recommendation generation, and prediction-history management in a unified web application. The objective is to provide an accessible platform for preliminary uterine cancer risk assessment while emphasizing the importance of consultation with qualified healthcare professionals for further evaluation.

5. PROPOSED SYSTEM

5. PROPOSED SYSTEM

The proposed AI-Based Uterus Cancer Risk Prediction and Decision Support System provides a preliminary method for evaluating uterine cancer risk from selected patient information. The system brings together patient-data processing, machine learning-based prediction, risk interpretation, recommendations, and record management within a single application. Machine learning is suitable for this type of application because it can examine several input variables together and learn associations from structured healthcare data [13][14].

5.1. System Architecture

The proposed architecture is organized into six major functional components: the user interface, patient-data collection, data preprocessing, AI-based prediction, risk classification and recommendation, and database management. Each component performs a specific task and contributes to the overall prediction process. The integration of these modules enables healthcare-related information to be processed systematically and the resulting prediction to be presented in an understandable form [15][16].

5.2. Patient Data Collection

Patient information is entered through a web-based form provided by the application. The system considers selected demographic, reproductive, metabolic, and lifestyle-related attributes that are relevant to uterine cancer risk assessment [17][18]. Bringing these attributes together enables the prediction module to evaluate the patient's information as a combined set rather than considering each factor independently.

5.3. Data Preprocessing

Before prediction, the information submitted by the user undergoes the required preprocessing operations. Numerical values are prepared in the appropriate numerical representation, while categorical inputs are transformed into a form that can be handled by the machine learning model. This step helps maintain consistency between the information supplied to the application and the format expected by the prediction model. Proper preparation of input data is important because the representation and quality of the data can affect machine learning performance [19][20].

5.4. AI-Based Prediction Module

After preprocessing, the prepared patient information is forwarded to the trained AI/ML model. The model examines the supplied characteristics using the patterns obtained during its training process and produces a preliminary prediction. The resulting output is then passed to the subsequent risk-assessment stage. Previous research has demonstrated the applicability of machine learning and deep learning

techniques in different cancer-related prediction and classification tasks [21][22].

5.5. Risk Classification Module

The prediction generated by the model is further interpreted by the risk-classification component. Based on the prediction score produced by the implemented model, the system assigns the result to one of the predefined categories: Low, Medium, High, or Critical. Converting numerical or model-generated outputs into recognizable categories makes the information easier for users without technical knowledge to understand [23].

5.6. Recommendation Module

Once the risk category has been determined, the recommendation component generates guidance corresponding to the obtained result. When the system indicates a higher level of risk, the user is advised to obtain further evaluation from a qualified healthcare professional. The recommendation functionality is intended to provide supportive information, while clinical decisions and diagnosis remain the responsibility of appropriate healthcare professionals [24][25].

5.7. Database and Prediction History

The application maintains user-related information and prediction records within a database. A stored assessment may include details such as the prediction result, confidence value, assigned risk category, recommendation, and other relevant assessment information. The prediction-history functionality enables users to access earlier results and provides a structured way of maintaining assessment records.

5.8. Web Application Interface

The complete system is deployed as a web application developed using Python and Flask. The interface connects the major functionalities of the system, including user authentication, patient-data entry, prediction, recommendation display, and prediction-history access. By providing these functions through a web interface, the proposed application offers users a straightforward way to interact with the prediction and decision-support components [26].

6. METHODOLOGY

The proposed system follows a structured workflow for converting patient information into a preliminary assessment of uterine cancer risk. The process begins with collecting the required patient attributes and continues through data preparation, feature handling, model-based prediction, risk interpretation, recommendation generation, and storage of the assessment results. Each stage contributes to the overall functioning of the proposed healthcare decision-support application. The methodology uses machine learning to examine multiple patient-related attributes and identify patterns relevant to cancer-risk assessment [19][20].

6.1. Data Acquisition

Patient information is obtained through the input interface of the web application. The application collects selected attributes related to demographic characteristics, reproductive history, lifestyle, and health conditions. Such characteristics have been examined in earlier studies in relation to

endometrial and uterine cancer risk [17][18]. After entry, the collected values are organized into a structured representation so that they can be passed to the subsequent processing stages.

6.2. Data Preprocessing

The information received from the user is prepared before it is supplied to the prediction model. Numerical inputs are converted into the required numerical representation, whereas categorical values are encoded when necessary. The application also considers incomplete or invalid entries during this stage. Consistent preprocessing helps ensure that the input supplied during prediction follows the format expected by the trained machine learning model [19][21].

6.3. Feature Preparation

The input variables required by the trained model are identified and arranged in the appropriate order before prediction. This stage ensures that only the relevant attributes are supplied to the model and that their representation corresponds to the format used during model development. Proper selection and organization of input features are important for obtaining meaningful results from machine learning-based healthcare applications [22][23].

6.4. AI-Based Prediction

Once the input has been prepared, it is supplied to the trained AI/ML model. The model processes the selected patient attributes and uses the patterns learned from the training data to produce the prediction outcome. The generated result is then forwarded to the risk-assessment stage for further interpretation. Machine learning techniques have been applied in cancer-related prediction and classification tasks because they can identify relationships among multiple patient characteristics [24][25].

6.5. Risk Score Generation

The output obtained from the prediction model is processed to determine the corresponding confidence or risk score. This value provides an indication of the model's confidence in the generated prediction and serves as an input for the subsequent risk-classification process. The score is therefore used to translate the model output into a form that can be presented more clearly to the user.

6.6. Risk Classification

The calculated score is interpreted using the predefined risk levels incorporated into the application. The proposed system represents the outcome using four categories: Low, Medium, High, and Critical. Assigning a descriptive category to the model output provides a simpler representation of the prediction and enables users without machine learning knowledge to understand the general risk level [26].

6.7. Recommendation Generation

After determining the risk category, the recommendation component selects and displays an appropriate informational message. When the assessment indicates an elevated level of risk, the system encourages the user to obtain further evaluation from a qualified healthcare professional. The recommendation is intended to provide supportive guidance, and the prediction should not be regarded as a replacement for professional clinical judgment [27][28].

6.8. Result Storage and History

Following completion of the prediction process, the assessment information is saved in the application's database. The stored information may include the user's details, prediction outcome, confidence value, assigned risk category, and corresponding recommendation. The history component uses these stored records to allow users to review their previous assessments when required.

6.8.1. Result Presentation

The prediction outcome is presented to the user through a dedicated result page in the web application. The displayed information includes the prediction, confidence value, assigned risk category, and recommendation. Presenting these elements together provides the user with a concise interpretation of the model output without requiring direct interaction with the underlying machine learning implementation.

6.8.2. Methodology Flow

The complete workflow of the proposed methodology can be summarized as follows:



figure 1: Methodology

7.SYSTEM ARCHITECTURE

The proposed system follows a layered architecture in which the major functional modules communicate with one another to complete the risk-assessment process. The architecture connects the web interface, application logic, data-processing unit, prediction model, risk assessment, recommendation mechanism, and database. Separating these functions into individual layers makes the application easier to organize and allows each component to perform its designated task within the overall workflow.

7.1. User Interface Layer

The user interface serves as the primary point of interaction with the application. Through this layer, users can create an account, log in, provide patient information, view prediction outcomes, read recommendations, and access previous assessment records. The interface is designed to present the system's outputs in a straightforward manner without requiring users to understand the internal machine learning operations [29][30].

7.2. Application Layer

The application layer acts as the connecting component between the frontend and the underlying system modules. It is developed using Python and Flask and is responsible for processing requests received from the user interface. This layer coordinates activities such as authentication, submission of patient information, prediction requests, generation of results, and retrieval of historical assessment records.

7.3. Data Processing Layer

The data-processing layer prepares the information received from the user for use by the prediction component. Depending on the input type, the data is transformed, encoded, and arranged according to the format required by the trained model. Maintaining a consistent representation of input data is important because machine learning models rely on properly prepared features to produce their outputs [19][21].

7.4. AI Prediction Layer

Following data preparation, the processed patient attributes are supplied to the trained AI/ML model. This layer is responsible for evaluating the input features and producing the corresponding prediction together with its associated confidence value. The use of machine learning enables the system to examine relationships among different characteristics within the cancer-related dataset [24][25].

7.5. Risk Assessment Layer

The prediction generated by the AI model is subsequently handled by the risk-assessment layer. This component interprets the model output and maps it to one of the predefined categories used by the application: Low, Medium, High, or Critical. Representing the prediction through descriptive risk levels provides a more accessible interpretation of the model output for users.

7.6. Recommendation Layer

The recommendation layer uses the prediction outcome and its assigned risk category to determine the informational guidance displayed to the user. When an assessment falls into a higher-risk category, the system advises the user to seek additional evaluation from a qualified healthcare professional. This component is intended to provide supportive information while ensuring that the system does not independently replace professional clinical judgment [27][28].

7.7. Database Layer

The database layer is responsible for maintaining user-related information and assessment records generated by the application. A prediction record may contain the obtained outcome, confidence value, risk category, recommendation, and other relevant assessment details. These stored records provide the information required by the prediction-history functionality when users access their previous results.

7.8. Overall Architecture

The interaction among the different components of the proposed system can be represented through the following flow:

The database also communicates with the application layer to support user authentication and retrieval of previous prediction records.



Figure 2: Overall System Architecture

8. AI/ML MODEL AND PREDICTION PROCESS

The prediction component forms the core of the proposed system and is responsible for processing the patient information submitted through the application. The overall process includes selecting the prediction approach, preparing the input data, generating the model output, assigning a risk category, determining the confidence value, and providing an appropriate recommendation.

8.1. Model Selection

A machine learning-based approach is adopted to process the selected patient attributes and generate an initial assessment of uterine cancer risk. The use of machine learning allows multiple input characteristics to be considered together, enabling the model to learn relationships between patient attributes and the corresponding prediction outcomes [30][31].

8.2. Model Training

The prediction model is developed using a structured dataset containing patient-related input attributes along with their corresponding target outcomes. During the training stage, the model is exposed to the available input features and learns patterns associated with the different outcome classes. The available data is separated into training and validation portions to assess the model during development. Maintaining a distinction between data used for learning and data used for evaluation helps provide a more meaningful assessment of model performance [32].

8.3. Input Feature Processing

Before an assessment is generated, the information entered through the web application is converted into the representation required by the trained model. Numerical variables are maintained in the appropriate numerical form, while categorical information is transformed when necessary. The preprocessing operations applied to new patient data follow the same approach used during model development so that the input remains consistent throughout the prediction process [33].

8.4. Prediction Process

After the input preparation stage is completed, the processed feature values are supplied to the trained machine learning model. The model evaluates these values using the patterns learned from the training data and produces the corresponding prediction. This output is subsequently forwarded to the risk-

assessment component, where it is interpreted and assigned to the appropriate risk category.

8.5. Risk-Level Determination

The model output is presented to the user through a predefined risk-level classification. The proposed application uses the following four categories:

- Low Risk
- Medium Risk
- High Risk
- Critical Risk

The classification provides a simplified representation of the prediction and enables users to understand the general level indicated by the system without having to interpret the raw model output.

8.6. Confidence Score

In addition to the predicted outcome, the system displays a confidence value associated with the model's prediction. This value provides supplementary information about the model's estimated certainty for the generated result. However, the confidence value represents a model output and should not be interpreted as confirmation of a clinical diagnosis or as clinical certainty [34].

8.7. Recommendation Generation

The prediction outcome and corresponding risk category are forwarded to the recommendation component. Based on the identified category, the system generates an informational message for the user. When the prediction indicates a higher level of risk, the application advises the user to seek additional assessment from a qualified healthcare professional.

8.8. Prediction Workflow

The complete prediction workflow of the proposed system can be summarized as:



Figure 3: Prediction workflow

9. IMPLEMENTATION

The proposed system is developed as a web-based application in Python using the Flask framework. The implementation connects the machine learning prediction component with the user interface, data-processing functions, and database services. Flask acts as the application framework through which information is exchanged between the frontend, prediction process, and stored records.

The application begins with user registration and authentication, after which the user can access the interface for entering the required patient information. The submitted

details are prepared according to the input format expected by the trained machine learning model and forwarded to the prediction component. Once the model processes the input, the resulting prediction and confidence value are obtained and supplied to the risk-assessment module for determining the corresponding risk category.

A recommendation facility is also incorporated into the application. Based on the risk category generated by the prediction process, the system displays an appropriate informational message. Details associated with the assessment, including the prediction outcome, confidence value, risk category, and recommendation, are maintained in the database. The Prediction History functionality allows users to retrieve and review their previously generated assessment results.

The implementation uses Python, Flask, HTML, CSS, machine learning libraries, and SQLite as the primary technologies. The system follows a modular design in which authentication, data preprocessing, prediction, risk assessment, recommendations, and database operations work together as different functional components of the application. The overall implementation sequence can be represented as:



Figure 4: Implementation workflow

The implemented application provides a convenient platform for preliminary uterine cancer risk assessment and presents the generated information in an accessible manner. The prediction is intended to provide supportive risk information, while diagnosis and treatment decisions remain under the responsibility of qualified healthcare professionals [35][36].

10. RESULTS AND DISCUSSION

The developed application was evaluated to examine whether the different system modules could work together to process patient information and produce a preliminary uterine cancer risk assessment. The testing focused on the complete application workflow, including patient-data processing, machine learning-based prediction, risk categorization, recommendation generation, and database operations.

For each assessment, the trained model receives the required patient attributes and produces a prediction together with an associated confidence value. The prediction output is then interpreted by the risk-assessment component and assigned to the corresponding risk category. This enables the system to present the model output in a more understandable form. Based on the resulting category, the recommendation component also provides suitable informational guidance to the user.

Functional testing was performed using different combinations of patient inputs to examine the behavior of the prediction and application modules. The major functions, including user login, patient-information submission, prediction generation, result presentation, database storage, and retrieval of previous assessments through the Prediction History feature, were observed to operate as intended during testing.

Overall, the testing demonstrates that the major components of the proposed web application can operate together as an integrated workflow for preliminary uterine cancer risk assessment. However, the system output should be regarded as supportive information and not as a substitute for professional clinical diagnosis.

10.1. Prediction Results

The assessment results generated by the system include the following information:

TABLE 1: Prediction Results

Output	Description
Prediction	Predicted cancer-risk outcome
Confidence	Model confidence associated with the prediction
Risk Level	Low, Medium, High, or Critical
Recommendation	Appropriate informational guidance

The results demonstrate that the proposed system can provide an integrated platform for preliminary risk assessment. However, the generated predictions are intended for decision support and awareness only and should not be considered a substitute for professional medical diagnosis [35][36].

10.2. Discussion

A key strength of the proposed system is that it brings together AI-based risk prediction, a web interface, risk-level assessment, personalized recommendations, and prediction-history management within one integrated platform. This provides users with a complete workflow rather than only a machine learning prediction.

The system also demonstrates the potential of machine learning for analysing multiple patient-related factors simultaneously. However, the reliability of the prediction depends strongly on the quality, size, representativeness, and diversity of the training dataset. Therefore, further validation using larger and clinically validated datasets is required before considering practical clinical deployment [37][38].

11. CONCLUSION

The proposed AI-Based Uterus Cancer Risk Prediction System provides a web-based approach for preliminary cancer risk assessment using patient-related information and machine learning techniques. The system integrates data preprocessing, AI-based prediction, risk classification, recommendation generation, and prediction-history management into a single platform.

The developed application provides users with a simple interface for entering relevant information and receiving a prediction with its corresponding confidence and risk category. The integration of recommendations and historical records further improves the usefulness of the system as a decision-support and health-awareness tool.

The proposed approach demonstrates the potential of artificial intelligence to assist in the early assessment of cancer-related risk. However, the system should be considered a supportive tool rather than a replacement for clinical diagnosis. The reliability of the results depends on the quality and diversity of the dataset used for model development. Future work can focus on larger clinically validated datasets, improved model architectures, extensive external validation, and integration of explainable AI techniques to make predictions more transparent and clinically interpretable [37][38].

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