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# FutureGen – Predicting Genetic Health

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***Abstract***

*FutureGen is an intelligent web-based system developed to help couples assess the risk of genetic disorders in their future child through data-driven analysis. The system brings together modern web technologies and machine learning to offer accurate and accessible predictions. The frontend, built with React, provides an intuitive interface for user interaction, while a Flask-based backend API handles model inference and manages communication with the Supabase database, which securely stores user and prediction data. The machine learning engine, powered by a Random Forest classifier, processes clinical and parental information such as age, carrier status, and family medical history to estimate the likelihood of hereditary disorders. By integrating AI with healthcare insights, FutureGen aims to promote early awareness, support genetic counseling, and assist couples in making informed family planning decisions.*

**Keywords:** Genetic disorder prediction, machine learning, parental health data, ai in healthcare, genetic risk assessment

## INTRODUCTION

Genetic disorders are inherited health conditions caused by abnormalities in DNA or gene mutations passed from parents to their children. With growing awareness of hereditary diseases, early prediction and prevention have become vital in supporting healthy pregnancies. Advances in artificial intelligence now enable data-driven systems to assess potential genetic risks even before conception. FutureGen is an AI-based web application developed to predict the likelihood of genetic disorders in a couple's future child. The system uses parental health information, genetic history, and demographic data as input to generate accurate risk predictions through a trained Random Forest model. It features a Reactbased frontend for user interaction, a Flask API for backend processing, and a Supabase database for secure data management. By integrating machine learning with healthcare, FutureGen provides an accessible platform for early genetic risk assessment. It aims to assist couples in making informed decisions, promote genetic awareness, and contribute to preventive healthcare practices.

## LITERATURE REVIEW

**Raza A. et al., 2022** [1]

This study addresses a multi-label, multiclass classification problem of genetic disorders (main classes: single-gene, mitochondrial, multifactorial) using genomic-/clinical-data. They propose a novel feature-engineering pipeline: probabilities from Extra Trees and Random Forest are added as features, and a classifier chain approach links multiple classifiers in sequence. Their best model (XGBoost) achieved a macro-accuracy of ~84% and an α-evaluation score ~92%.

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**Yalçın E. et al., 2025** [2]

This work focuses on first-trimester screening for Down syndrome (Trisomy 21) using biochemical markers (PAPP-A, free β-hCG, NT) and transforms 1D patient data into 2D barcode

 

images for transformer-based deep-learning. They demonstrate improved accuracy for risk stratification (high/medium/low) using this hybrid AI approach.

**Bracher-Smith M. et al., 2021** [3]
A systematic review of ML methods applied to genetic prediction of psychiatric disorders (schizophrenia, bipolar, autism). They reviewed 13 studies, 77 models; AUCs ranged widely (~0.48 to 0.95). They found pervasive high risk of bias (PROBAST) and frequent methodological issues such as predictor leakage, inadequate validation, and poor reporting.

**Raben T. et al., 2021** [4]
This review explores polygenic risk scores (PRS) and genomic prediction of complex traits/diseases. It demonstrates that for some traits (e.g., height) prediction is feasible, but for many diseases performance remains modest. It underscores challenges: genetic architecture, sibling validation, large cohorts, and data limitations

**Yousaf M. B. et al., 2024** [5]
This research proposes a ML system for predicting genetic disorders (e.g., cystic fibrosis, diabetes, cancer) using decision tree and Naïve Bayes models on tabular data combining genetic, lifestyle and environmental features. It supports the concept of "multi-factorial input" rather than only genetics.

**Bahado-Singh R.O. et al., 2019** [6]
This study investigated whether DNA methylation (epigenomic) data from neonatal blood can be used to predict cerebral palsy using deep learning and AI models. The authors applied convolutional neural networks and achieved over 90% accuracy in distinguishing at-risk neonates.

**Naik S. et al., 2022** [7]
This paper built several ML models (Decision Tree, Random Forest, SVM) to predict genetic disorders from a medical dataset including family history, symptoms, and genetic traits. The Random Forest model yielded the highest accuracy (~92%)

**Shetty H.P., Patil M.S., Yadav S. et al., 2024** [8]
This comprehensive review discusses the integration of AI and ML in prenatal screening, genetic analysis, and early disease detection. It covers algorithms used for NIPT data interpretation, ultrasound analysis, and risk stratification, and also highlights ethical and privacy challenges.

## SYSTEM ARCHITECTURE

The proposed FutureGen System is designed with a modular architecture to ensure scalability, accuracy, and data security in predicting potential genetic disorders in unborn children. The system comprises multiple interconnected layers, each responsible for a distinct stage in the data processing and prediction pipeline.

### Input Layer

The Input Layer is the starting point of the system, responsible for collecting and accepting all relevant patient information. This includes genetic test summaries, demographic details such as age, gender, and ethnicity, and family medical history that could indicate hereditary risks.

Users (couples, doctors, or genetic counselors) provide this data through a web interface or directly via uploaded CSV files. The system may also support input from laboratory test results such as NIPT (NonInvasive Prenatal Testing) and biochemical markers like PAPP-A or β-hCG.

This layer ensures that all the required inputs are properly formatted and ready for preprocessing. Its goal is to standardize the incoming information, minimizing errors caused by inconsistent or missing data entries.

 

**Preprocessing Module**

The Preprocessing Module is a crucial intermediate layer where the raw input data is prepared for analysis. It performs several key operations such as data cleaning, normalization, and feature encoding. Data cleaning removes inconsistencies, fills in missing values, and handles outliers. Normalization scales all numeric values to a uniform range, ensuring that no single feature disproportionately affects the model. Categorical values, such as genetic marker types or risk indicators, are converted into numerical representations using label encoders.

By the end of this stage, the data is transformed into a consistent, machine-readable format suitable for feeding into the model. This layer significantly improves model accuracy and reliability by ensuring the quality and uniformity of the input dataset.

**ML Engine / Flask API**

The Machine Learning Engine, integrated through a Flask API, is the computational core of the system. This layer hosts the trained machine learning model specifically a Random Forest Classifier which has been developed using a labeled dataset containing historical patient data and known genetic outcomes.

The Flask API acts as the bridge between the user interface and the ML model. When input data is submitted, the API loads the trained model files (random_ forest_ genetic. pkl, scaler. pkl, and label_ encoders. pkl) and runs inference on the preprocessed data. The Random Forest algorithm was chosen for its robustness, ability to handle both categorical and continuous data, and superior performance on medical prediction tasks. This layer outputs the model's computed probabilities and classification results, such as whether the risk of a genetic disorder is low, moderate, or high.

**Prediction Engine**

The Prediction Engine interprets and categorizes the results obtained from the ML model. It assigns a risk level classification for the potential genetic disorder, based on thresholds derived from model probabilities.

For example, if the model predicts a 0-40% probability, the case is classified as "Low Risk," 40-70% as "Moderate Risk," and 70100% as "High Risk." This classification helps clinicians and users understand the prediction in a clear and actionable format. In some implementations, this layer can also generate explainable AI (XAI) insights, showing which features (such as maternal age or genetic marker values) contributed most to the prediction. This enhances transparency and supports medical decision-making.

**Output Layer**

The Output Layer is responsible for presenting the final results to users through interactive dashboards or automated reports. Users can view visual summaries such as graphs, probability bars, and categorized outputs that indicate the predicted risk level of genetic disorders. This layer is designed for interpretability and clarity, providing doctors or genetic counselors with actionable information that can guide clinical recommendations.

The output can also be downloaded as a report in formats like PDF or CSV for record-keeping or further analysis.

**Storage Layer**

The Storage Layer ensures secure and structured data management using a Supabase database, which is built on PostgreSQL. It stores patient data, prediction results, model logs, and system metadata.

This layer plays a vital role in maintaining data privacy, traceability, and version control. Every prediction request, along with its corresponding inputs and outputs, is stored securely for potential model retraining and audit purposes.

 

Supabase also provides authentication, encryption, and access control, making it suitable for handling sensitive healthcare data while complying with data protection standards.

Together, these layers create a seamless workflow starting from patient data entry, through preprocessing and machine learning-based prediction, to user-friendly risk reports all while ensuring data integrity and system scalability. The modular design allows for future expansion, such as integrating additional biomarkers, advanced deep learning models [9], or connecting with hospital databases for realtime updates (Figure 1).

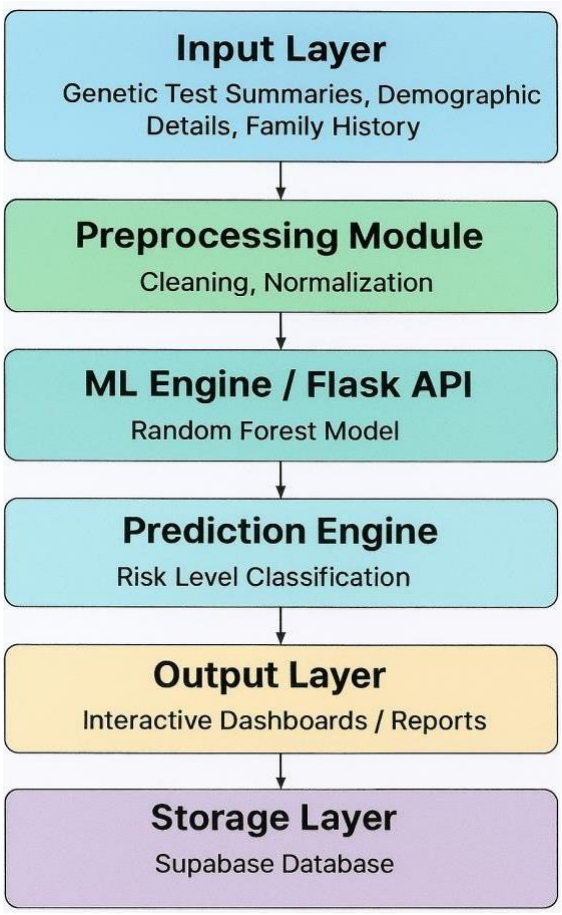


**Figure 1.** FutureGen system.

## ARCHITECTURE

### Working of the System

The FutureGen system functions as an intelligent, modular platform designed to predict possible genetic disorders in a child before birth. It brings together machine learning, secure cloud storage, and interactive dashboards to create a smooth experience for both patients and doctors.

Every component in the system works in sequence beginning from user registration and ending with result generation to ensure the predictions are accurate, personalized, and easy to interpret. The workflow can be broadly divided into several stages, as discussed below.

### User Registration and Role-Based Access

The system begins with the sign-in/sign-up process, allowing users to access FutureGen according to their designated roles-Patient or Doctor. When a new patient visits the platform, they must first register

 

by entering their personal details such as email, and password. Once registered, they can log in to their dashboard using valid credentials.

In contrast, doctors are pre-registered by the system administrator and can sign in directly. Role-based authentication ensures that patients and doctors only access the data relevant to them.

This process is handled securely through the Flask backend API, which verifies login credentials stored in the Supabase cloud database. Once verified, users are redirected to their respective dashboards

- *For Patients:* New users are required to register by creating an account using basic information such as their full name, email, and password. Once registered, they can securely log in to the system using their credentials. The authentication process verifies the details against the Supabase database to prevent unauthorized access.
- *For Doctors:* Doctors are pre-registered by the system administrator and can log in directly using their assigned credentials. Unlike patients, they do not need to sign up manually. After successful login, each user is directed to their respective dashboard:
- The Patient Dashboard provides functionalities to upload reports, track their analysis status, and view prediction outcomes.
- The Doctor Dashboard serves as an analytical workspace where doctors can view patient submissions, assess model outputs, and share professional insights.
- This role-based access system is managed through Flask's authentication mechanism integrated with Supabase, ensuring secure sessions, encrypted passwords, and controlled data visibility. This approach guarantees that patient data remains private while allowing doctors to view only the necessary medical details.

**Patient Data Upload and Validation**

Once authenticated, the patient initiates the process by uploading their medical or genetic data file, typically in CSV format. These files contain clinical and demographic parameters such as.

- Parental age and family medical history
- NT measurement (Nuchal translucency)
- β-hCG (Beta Human Chorionic Gonadotropin) levels
- PAPP-A (Pregnancy-Associated
- Plasma Protein A)
- Other derived genetic or biometric indicators

Upon upload, the system performs an automatic data validation process. This validation checks for missing entries, incorrect data types, or inconsistencies in uploaded files. Any data that fails validation is either flagged for correction or rejected with an appropriate message to the user.

Only cleaned and verified data is forwarded to the next module. This ensures that the system receives reliable input, thereby enhancing the accuracy of downstream machine learning predictions. All uploaded reports are securely stored in the Supabase cloud storage, where they are linked to the respective patient ID for easy retrieval. This storage mechanism supports real-time access for doctors, enabling instant review once the data is submitted.

**Doctor Dashboard and Record Management**

Once a patient uploads their report, it becomes visible on the Doctor Dashboard, which serves as the control panel for healthcare professionals. The doctor can browse through all submitted reports, filter them by patient name, date, or disorder category, and access each record for detailed review.

For each patient's report, the doctor can view

- The raw input data submitted by the patient.
- The machine learning analysis is performed by the model.
- The final predicted genetic risk level.

 

Doctors can also add remarks, interpretations, or medical advice based on the AI-generated predictions. This creates a collaborative workflow, where artificial intelligence provides analytical support and the doctor provides medical judgment [10].

In addition, the system keeps a record of all activities such as uploads, analyses, and reviews ensuring traceability and transparency in every operation.

**Data Preprocessing and Feature Preparation**

After patient data passes the validation stage, it is processed by the Preprocessing Module, which performs data transformation and normalization. This step is crucial because raw medical data often contains missing values, varying scales, and categorical features that cannot be directly used by machine learning algorithms. The Preprocessing Module carries out the following steps.

- *Data Cleaning:* Removes duplicate records and fills missing values using statistical imputation or model-based estimation.
- *Encoding Categorical Data:* Converts non-numeric features (like gender or family history) into numeric form using label encoders stored in label encoders.pkl.
- *Normalization and Scaling:* Applies Min Max Scaler or Standard Scaler
- (from scaler.pkl) to bring all numerical features to a comparable range, ensuring balanced influence during model training and prediction.
- *Feature Extraction:* Selects only the relevant parameters that significantly contribute to the model's predictive accuracy, based on previous training data from
- Genetic_Prediction_Dataset.csv.

By executing these steps, the Preprocessing Module transforms unstructured patient input into a structured, machine-readable format suitable for the prediction model.

**Machine Learning Model Execution**

At the core of FutureGen lies its Machine Learning Prediction Engine, which is responsible for generating genetic health predictions based on patient data. This module utilizes a Random Forest Classifier, pre-trained on a diverse dataset of genetic and clinical attributes. When new data is processed, the system loads the serialized model (random_forest_genetic.pkl) and performs real-time inference. The model evaluates the relationships between clinical parameters such as NT measurement, βhCG, and PAPP-A to predict the probability of genetic anomalies.

The output generated by the model consists of:

- A predicted risk category (e.g., Low Risk, Moderate Risk, or High Risk).
- A probability score associated with each prediction.
- Key feature contributions, indicating which factors most influenced the result.

This prediction is computed instantly using Flask's backend logic and returned to the system for visualization and reporting.

The use of a Random Forest model ensures interpretability, robustness against overfitting, and high accuracy in classifying genetic health conditions based on realworld data.

**RESULT VISUALIZATION AND REPORTING**

Once predictions are generated, they are displayed through interactive dashboards tailored to the user's role.

- On the Patient Dashboard, the output is presented in a clear, understandable format. Patients can view a summary of their predicted genetic risk, a probability score, and explanatory notes provided by the doctor.
- On the Doctor Dashboard, results are displayed with greater analytical depth, including feature importance graphs, prediction breakdowns, and comparative statistics.

 

Visualizations are rendered using integrated web technologies such as Bootstrap, Chart.js, and Flask templates, which make data insights easy to interpret. Each analyzed report is automatically saved in the database, creating a permanent medical record that can be accessed by both the patient and doctor anytime (Figure 2).

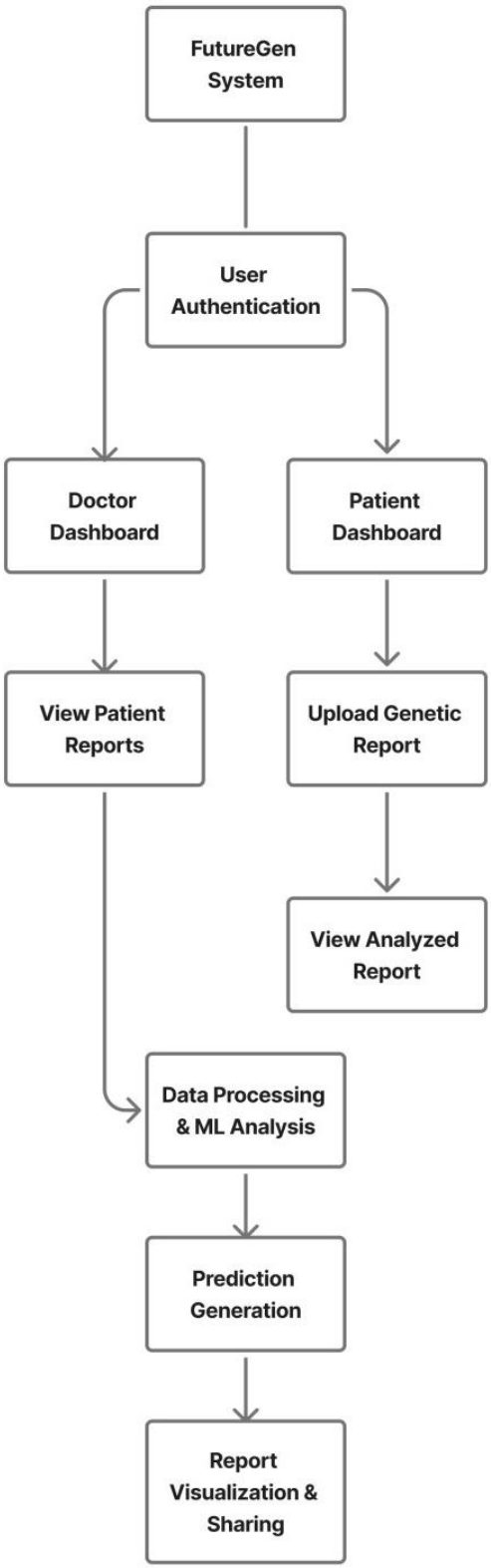


**Figure 2.** Flow of futuregen system.

 

**Doctor Review and Feedback Sharing**

Following model prediction, the doctor plays a vital role in reviewing the AI-generated analysis. Doctors can examine the underlying data, verify prediction accuracy, and add clinical feedback before finalizing the report.

After the doctor's approval, the verified report is shared with the patient through the system. This ensures that patients receive medically reviewed results, rather than raw algorithmic outputs.

The final report may also include medical recommendations, next-step advice (such as advanced diagnostic tests), and guidance for preventive care.

This human-in-the-loop approach enhances both accuracy and trust, blending computational intelligence with clinical expertise.

**Data Security, Privacy, and Continuous Learning**

FutureGen places strong emphasis on data privacy and integrity, particularly since it deals with sensitive medical information. All user data and files are securely stored in Supabase, which provides encryption at rest and in transit. Access control policies ensure that:

- Patients can only view their own reports.
- Doctors can only view patient data assigned to them.
- All interactions are logged for accountability.

Moreover, FutureGen is designed with scalability and adaptability in mind. As more patient data becomes available, the model can be retrained periodically to improve its accuracy, incorporate new biomarkers, or adapt to evolving genetic studies.

This feedback-driven enhancement ensures that FutureGen continues to evolve into a smarter, more precise predictive healthcare assistant (Figures 3–9).

**SYSTEM SCREENS**

**User Registration - Create Account**

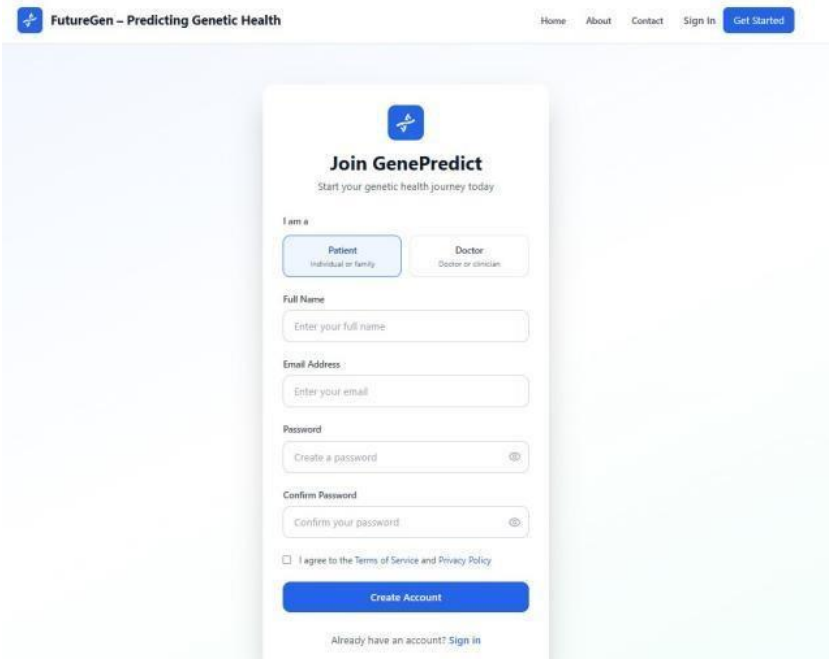


**Figure 3.** Patient sign in.

 

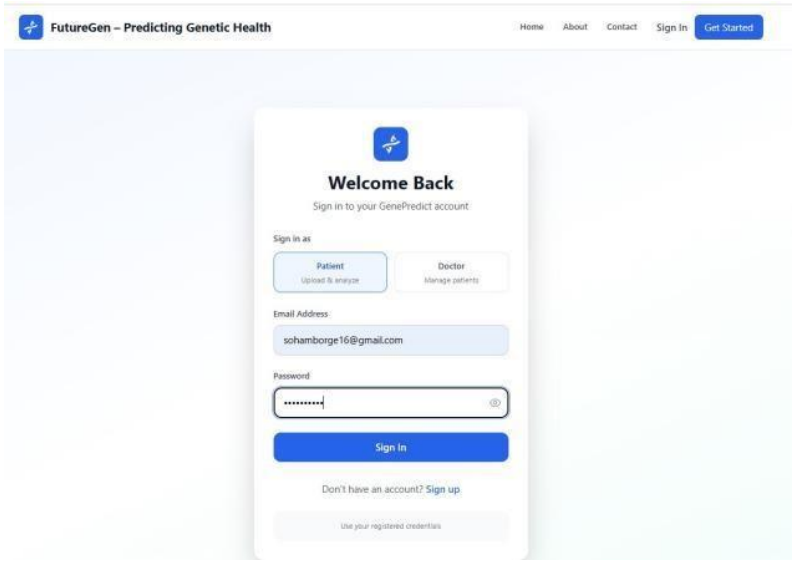


**Figure 4.** Doctor login.

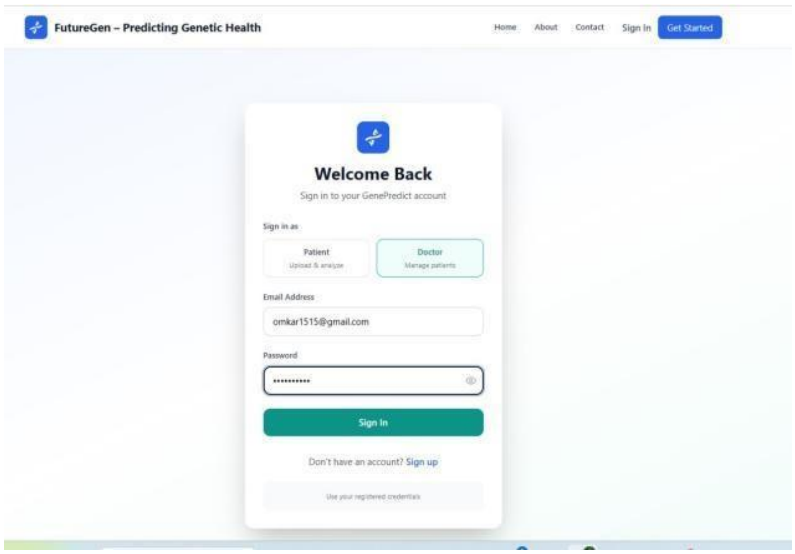


**Figure 5.** Patient dashboard.

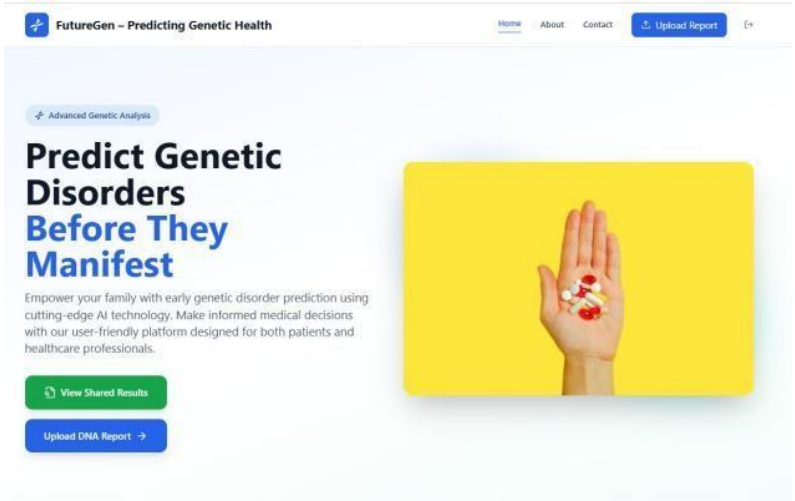


**Figure 6.** Upload DNA reports.

 

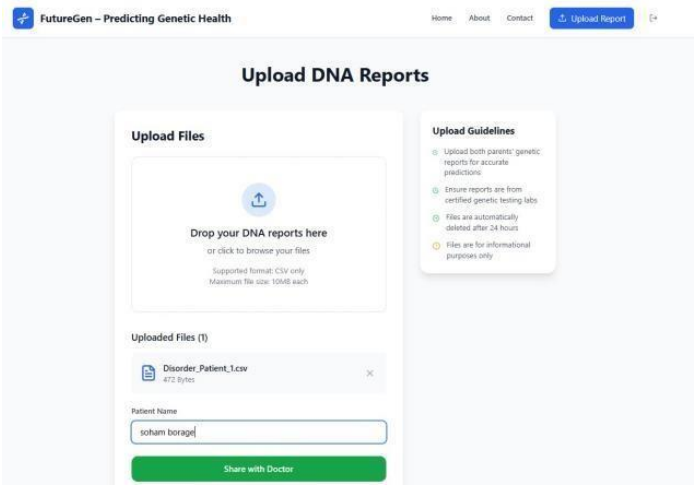


**Figure 7.** Doctor's dashboard.

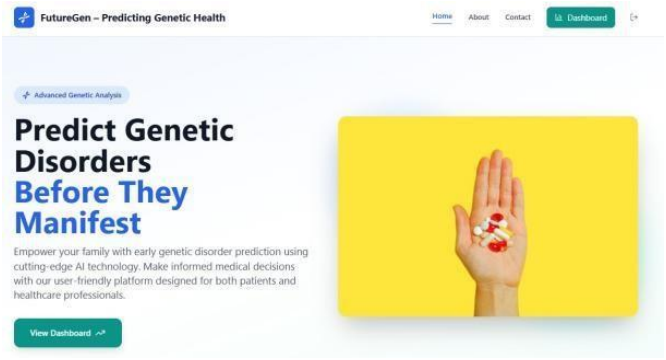


**Figure 8.** Uploaded reports in Doctor's dashboard.

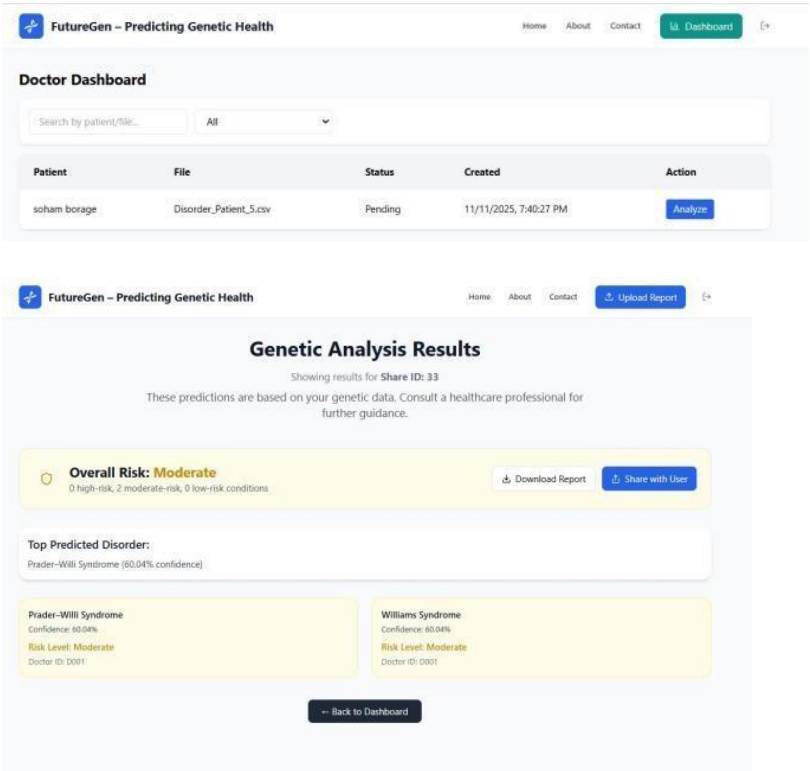


**Figure 9.** Genetic analysis result applications.

 

**Hospitals and Healthcare Centers**

FutureGen can be integrated into hospital systems to assist doctors in early detection of genetic risks, enabling preventive care and informed clinical decisions. Through EMR integration, physicians can access patient history and real-time predictive insights, improving diagnosis and treatment planning.

**Diagnostic and Genetic Testing Laboratories**

In diagnostic labs, FutureGen automates genetic data interpretation and report generation, reducing manual effort and error. Its machine learning models continuously refine predictions with new data, improving the reliability of genetic test results and overall lab efficiency.

**Research and Academic Institutions**

Academic and research organizations can use FutureGen to study relationships between genetic variations and diseases. It serves as an educational and experimental platform for projects in genomics, bioinformatics, and AI-driven healthcare.

**Pharmaceutical and Biotech Industries**

FutureGen supports pharmacogenomics by helping identify genetic markers that influence drug response. It can be used in drug discovery, patient stratification, and the development of personalized therapies, accelerating innovation in precision medicine.

**Public Health and Government Organizations**

Health agencies can employ FutureGen for large-scale genetic screening and early disease prediction programs. The system's data analytics can help design preventive healthcare policies and improve public health outcomes.

**Telemedicine and Digital Health Platforms**

FutureGen can be integrated into telehealth systems, allowing patients to upload genetic data for remote analysis and consultation. Its secure dashboards enable doctors to share insights digitally, enhancing accessibility and convenience in modern healthcare delivery.

**ADVANTAGES**

- *Early Disease Detection:* The system's predictive model identifies potential genetic disorders at an early stage, enabling proactive healthcare planning and timely medical intervention. This significantly improves the chances of managing or preventing severe health outcomes.
- *Efficient Data Analysis:* By leveraging advanced machine learning algorithms, FutureGen automates the analysis of complex genetic data. This minimizes manual effort, reduces human error, and ensures accurate, data-driven insights for both patients and doctors.
- *Simplified User Interaction:* The dual dashboard interface separate for patients and doctors makes the system user friendly and accessible. Patients can easily upload their genetic reports, while doctors can seamlessly view and interpret analyzed results through an intuitive interface.

**Enhanced Doctor–Patient Collaboration**

The platform bridges the communication gap between patients and healthcare professionals. Through real-time access to processed reports and predictions, doctors can provide personalized advice and share detailed insights directly with patients.

- *Secure Data Management:* FutureGen ensures privacy and data protection through secure authentication and controlled access. Sensitive patient data and medical reports are encrypted, maintaining confidentiality and compliance with healthcare data standards.
- *Scalable and Adaptable System:* The architecture of FutureGen allows easy integration of new genetic datasets, diseases, or predictive models, making it adaptable for future advancements in genetic research and healthcare analytics.

 

- *Time and Cost Efficiency:* Automating report processing and disease prediction reduces dependency on manual genetic testing and long analysis cycles, leading to faster results at lower operational costs.

## LIMITATIONS

- *Dependency on Data Quality:* The accuracy of predictions largely depends on the quality and completeness of the genetic data provided. Inconsistent, missing, or noisy data can lead to incorrect predictions or unreliable analysis results.
- *Limited Dataset Availability:* Since genetic datasets are often confidential and difficult to obtain, the model's training and testing are limited to available sample data. This restricts the system's ability to generalize results across diverse populations or rare disorders.
- *Computational Requirements:* Processing and analyzing large genetic datasets using machine learning models require significant computational power and storage. This may limit system performance on low-end hardware or cloud dependent environments.

### Lack of Real-Time Medical Validation

The system's predictions are based on data-driven algorithms rather than direct medical diagnosis. Without real-time validation or approval from certified medical professionals, the results should be treated as supportive insights rather than final medical conclusions.

- *Ethical and Privacy Concerns:* Handling genetic data involves sensitive personal information. Any breach or misuse of such data could lead to ethical concerns, even with encryption and secure authentication in place.
- *Restricted to Structured Input Format:* The system currently supports report uploads in structured formats (e.g., CSV). It may not handle unstructured medical data such as scanned reports or handwritten records without additional preprocessing modules.

## CONCLUSION

*FutureGen:* Predicting Genetic Health marks a progressive step toward integrating artificial intelligence into the realm of genetic analysis and personalized medicine. By leveraging machine learning and automated data processing, the system enables early risk prediction and supports healthcare professionals in understanding genetic predispositions more effectively. The use of interactive dashboards, secure authentication, and an intuitive interface ensures that both patients and doctors can easily access and interpret health insights with confidence.

Through its seamless workflow from data upload to predictive visualization FutureGen minimizes manual effort, enhances accuracy, and contributes to datadriven decision-making in clinical settings. The system's modular architecture allows scalability and adaptation for various genetic and diagnostic studies, making it a valuable tool for research institutions and healthcare organizations alike.

In the future, FutureGen can be extended with features like real-time genomic data integration, cloud-based medical collaboration, and advanced AI interpretability models to make genetic predictions even more reliable and explainable. Overall, FutureGen represents a vital advancement toward predictive healthcare empowering individuals and medical professionals to move from reactive treatment to proactive health management.

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