Asthma Diagnosis Aid Tool for Doctors

Group 7

Project Goals

The goal of the project was to develop a tool for physicians to use in the diagnosis and treatment of asthma patients. Specifically, a model was trained to predict the probability of a person having asthma, taking into consideration their lifestyle, medical history, and symptoms.

Intended Target Audience

The target audience of the tool are doctors. The tool is designed to help them to diagnose patients in a structured and consistent way, while coping with time constraints. The application is designed so that doctors can understand the underlying logic of the prediction process without any advanced data science background.

Dataset and Its Documentation

The model was trained on *The Asthma Disease Dataset*[1], first published by user Rabie El Kharoua on Kaggle in 2024. The original dataset contains extensive health information on 2,392 patients, including their demographics, lifestyle and habits, medical history, relevant clinical measurements, symptoms, and asthma diagnosis. There are 28 variables in total, though not all of them were relevant for model training.

Some variables were treated as protected, such as *Gender*, *Age*, *Ethnicity*, *FamilyHistory*, and *EducationLevel*. To check if the model discriminates against patients based on these features, fairness metrics were calculated and provided to users of the app.

The target variable is *Diagnosis*, which takes the value *Yes* if a patient has asthma and *No* if they do not. The target distribution is imbalanced, with 2,268 patients without asthma and only 124 patients with asthma. The classes were further balanced using an oversampling procedure, which is also mentioned in the model description.

Key Design Decisions

The design process was guided by the goals of the tool, which were aimed at meeting doctors' demands. It was important not only to create a tool that aids in decision-making but

[1] The link to the original dataset: https://www.kaggle.com/datasets/rabieelkharoua/asthma-disease-dataset

also to ensure that it is explainable. Doctors should be able to understand how the model makes predictions, what data it was trained on, and whether they should trust it.

The development of the app proceeded over several stages. First, the prototype of the app was created in Figma after team brainstorming sessions. Then, some changes were applied after a peer review. The interface was created with Streamlit and further tested using the think-aloud method. The final corrections to the app and its interface were implemented after considering the comments of a potential app user.

To enable users to easily and intuitively navigate through the app[2], the following pages were created:

- **Homepage**: A welcoming page that introduces the app to the user.
- **Prediction Page**: A form that users fill out to obtain predictions and accompanying interpretation of the results.
- **Model Description**: An explanation of the training process, performance metrics, fairness metrics, and other relevant information.
- **Dataset Description**: An overview of the dataset on which the model was trained, including variable distributions.
- **Call for Feedback**: A feature that allows users to contribute to the app's further development.

We would like to highlight the following design decisions made while developing the app:

- **Intuitive User Interface:** The application includes a straightforward side menu, making navigation simple and user-friendly. Additionally, on the homepage, we included a page overview to familiarize users with the content of each page.
- **Disclaimer:** The disclaimer is prominently displayed at the beginning of the homepage to ensure that users see it before using the tool. It highlights all the important points users need to consider before using the tool.
- **Detailed Explanations:** The tool provides very detailed explanations of various data science concepts, such as the interpretation of model predictions, evaluation results, fairness metrics, and both global and local explanations of the model.
- **Reliability of Predictions:** After a prediction is made, the tool offers multiple methods to help doctors assess the reliability of the prediction. This includes the prediction probability, a PCA-based similarity check with the training dataset, and local explanations that highlight the contribution of each feature to the prediction.
- **Fairness Evaluation:** The application includes a fairness evaluation section to ensure the model treats different demographic groups equitably. Explanations of fairness metrics are provided before allowing users to select a metric for analysis.

[2] The screencast of the app is available here: https://box.fu-berlin.de/s/YrQ6W6m8r7qYQFC

Problems We Faced

One of the problems we faced in the early stages of the project was the lack of clear definitions for some of the variables. For example, several variables related to lifestyle (diet quality, sleep quality, dust exposure, etc.) have values ranging from 0 to 10, but the logic behind this categorization was not provided in the metadata. Ideally, doctors would have proper guidance on how to navigate these scales. However, we assumed the existence of abstract medical guidelines that they should consider when assessing their patients.

While designing the app interface, the main challenge was to minimize the complexity of the explanations. To make the model's predictions clear and intelligible to doctors who may not have a data science background, we aimed to provide simpler but consistent explanations and interpretations in a comprehensive manner. The same applies to implementing and explaining fairness metrics – we needed to ensure that doctors could understand and utilize these metrics effectively, which required careful consideration and design.

Reflections on the Development Process

We overcame the challenges by first presenting the prototype of the app to our colleagues and then testing the app with a potential user.

Feedback from another group helped refine the prototype. For example, a disclaimer was added to the homepage to warn users about potential inaccuracies in predictions and biases in the original data (such as the presence of only three categories in the *Ethnicity* variable or the ambiguity of the *Smoking* status). Additionally, the Prediction page was supplemented with exemplary inputs and an info section for each variable was added to ensure the user understands what needs to be inputted and fill it in the appropriate format to avoid errors.

A UI test helped us understand the problems a potential user might face. Based on the results of the test, we edited the explanatory texts (e.g., elaborated on the differences between local and global explanations) and slightly changed the layout of some pages (e.g., moved the definition of fairness metrics before the drop-down menu allowing users to try them). Moreover, we ensured that user input values are retained on the Prediction page when navigating between pages. This allows users to switch to different pages, such as to analyze data distributions, without losing their entered information.

Our main challenge was ensuring that users could understand the various features and explanations. Therefore, we prioritized transparency by providing clear explanations and accurate evaluation results so doctors can trust the tool and understand its strengths and weaknesses.