AI Boot Camp Project 3

Symptom-Based Disease Prediction Model

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Project Description

- This project aims to create a machine-learning model capable of predicting diseases based on user input symptoms.
- The model will use a reliable dataset, the Symptom-Disease Prediction Dataset (SDPD), to train and evaluate predictive algorithms.
- Output will include a customer-facing app that provides preliminary diagnoses and possible remedies based on the symptoms provided by the user.

Project Goals

- Develop a disease prediction model, based on symptoms
- Pilot a UI/UX application for users to input symptoms

Dataset/ Data Extraction

- **Dataset**: Symptom-Disease Prediction Dataset (SDPD)
- **Source**: Tucker, Jay (2024), "SymbiPredict", Mendeley Data, V1, doi: 10.17632/dv5z3v2xyd.1
- **Description**: A comprehensive and structured dataset linking symptoms to various diseases, rated as "reliable" by medical institutions and professionals, including the CDC.
- **Format**: CSV

Data Cleaning & Preprocessing

- Different format data was looked at
- Cleaned data to replace NaN values with 0s
- Visualized dataset for diseases, symptoms, occurrence frequencies)
- Normalizing and encoding symptom data.

Cleaned Dataset: SymbiPredict

silver_like_dusting	small_dents_in_nails	inflammatory_nails	blister	red_sore_around_nose	yellow_crust_ooze	prognosis
0	0	0	0	0	0	Hypoglycemia
1	1	1	0	0	0	Psoriasis
0	0	0	0	0	0	Osteoarthritis
0	0	0	0	0	0	Bronchial Asthma
0	0	0	0	0	0	Hyperthyroidism

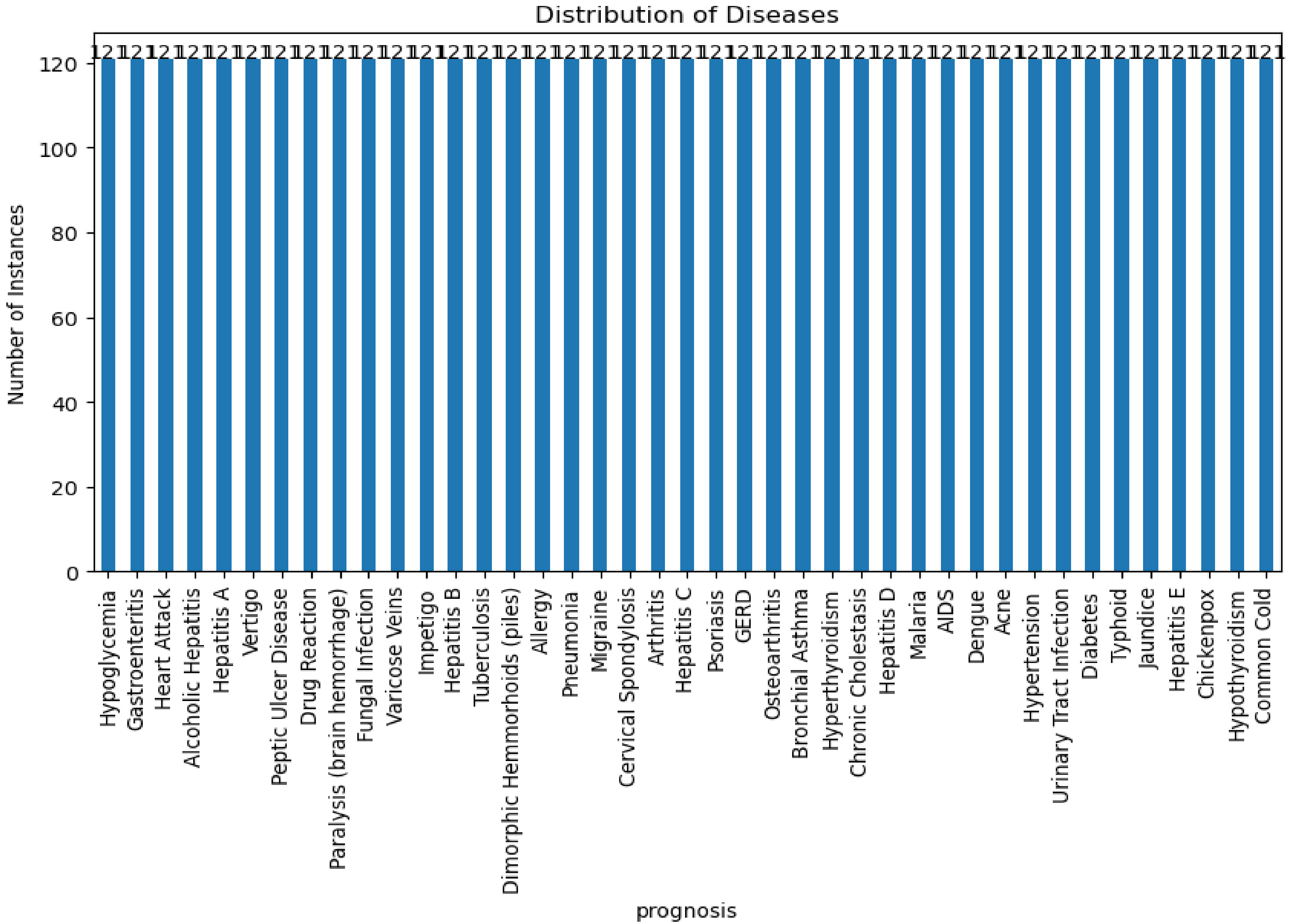
Cleaned Dataset: DiseasePredict

	Disease	Symptom_1	Symptom_2	Symptom_3	Symptom_4	Symptom_5
4379	Hypoglycemia	vomiting	fatigue	anxiety	sweating	headache
393	Psoriasis	skin rash	skin peeling	silver like dusting	small dents in nails	inflammatory nails
1164	Osteoarthritis	joint pain	neck pain	hip joint pain	swelling joints	0
4478	Bronchial Asthma	fatigue	cough	high fever	breathlessness	family history
731	Hyperthyroidism	fatigue	mood swings	weight loss	restlessness	sweating

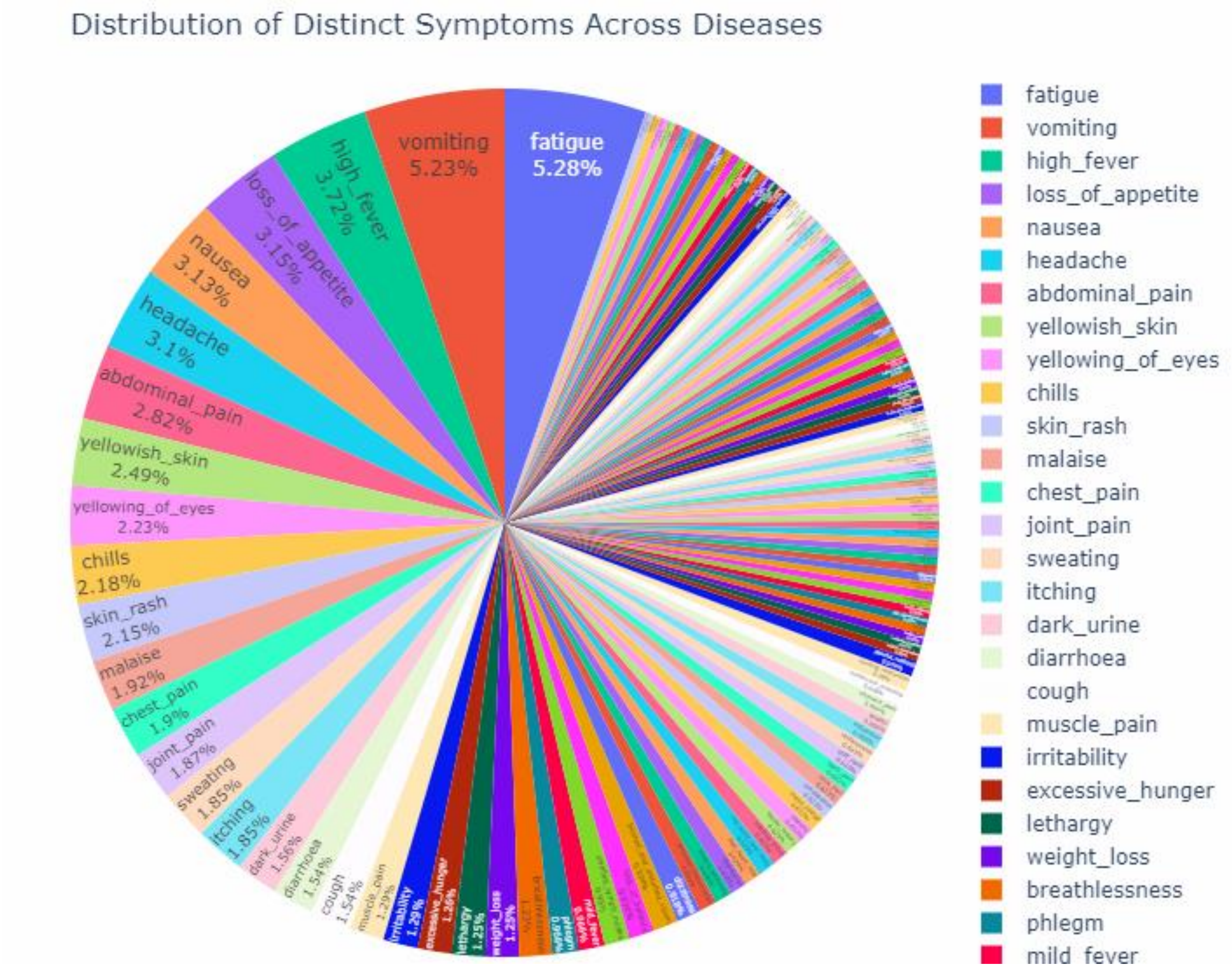
Exploratory Data Analysis

- Visualized key feature distributions and their relationships
- Examined correlations between variables.
- Identified top attributes such as ` disease’ and ‘symptom out of 41 diseases and 132 symptoms
- Visuals on the next slides:

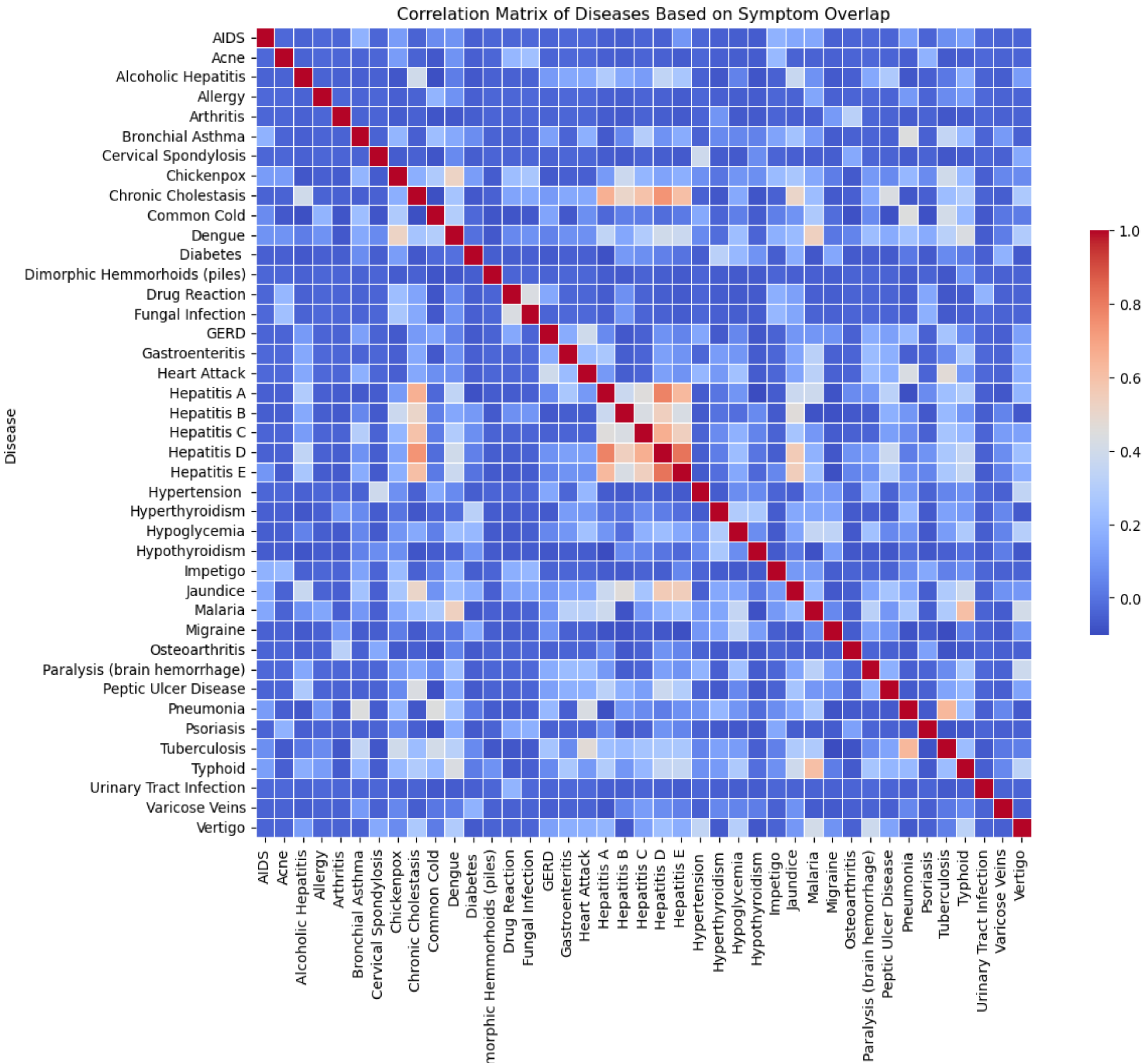
Model Output



Model Output



Model Output



Project Methodology

Approach taken to achieve goals

- Split data into training and testing sets.
- Feature Importance
- Splitting the dataset into training, validation, and testing subsets.

Model Optimization & Evaluation

Model Optimization and Evaluation (accuracies of all models) 1.0

- Three models—MLP, CNN, and RNN with LSTM

  Scaled features using ‘OneHotEncoder’---ordinal variables(copy)

Model Optimization & Output

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Model	Training		Testing	
	Accuracy	Loss	Accuracy	Loss
MLP	1.00	6.40E-05	1.00	5.34E-05
CNN	1.00	2.94E-06	1.00	2.44E-06
RNN with LSTM	0.0282	3.71	0.0243	3.713

-1ML

Result/Conclusion Of Models -- MLP, CNN, RNN with LSTM

- MODEL PERFORMANCE: MLP, CNN, RNN with LSTM
- CNN Model performed best--high accuracy, low loss
- MLP also performed well, with slightly lower test accuracy
- RNN with LSTM did not perform well, perhaps not the right choice for this dataset

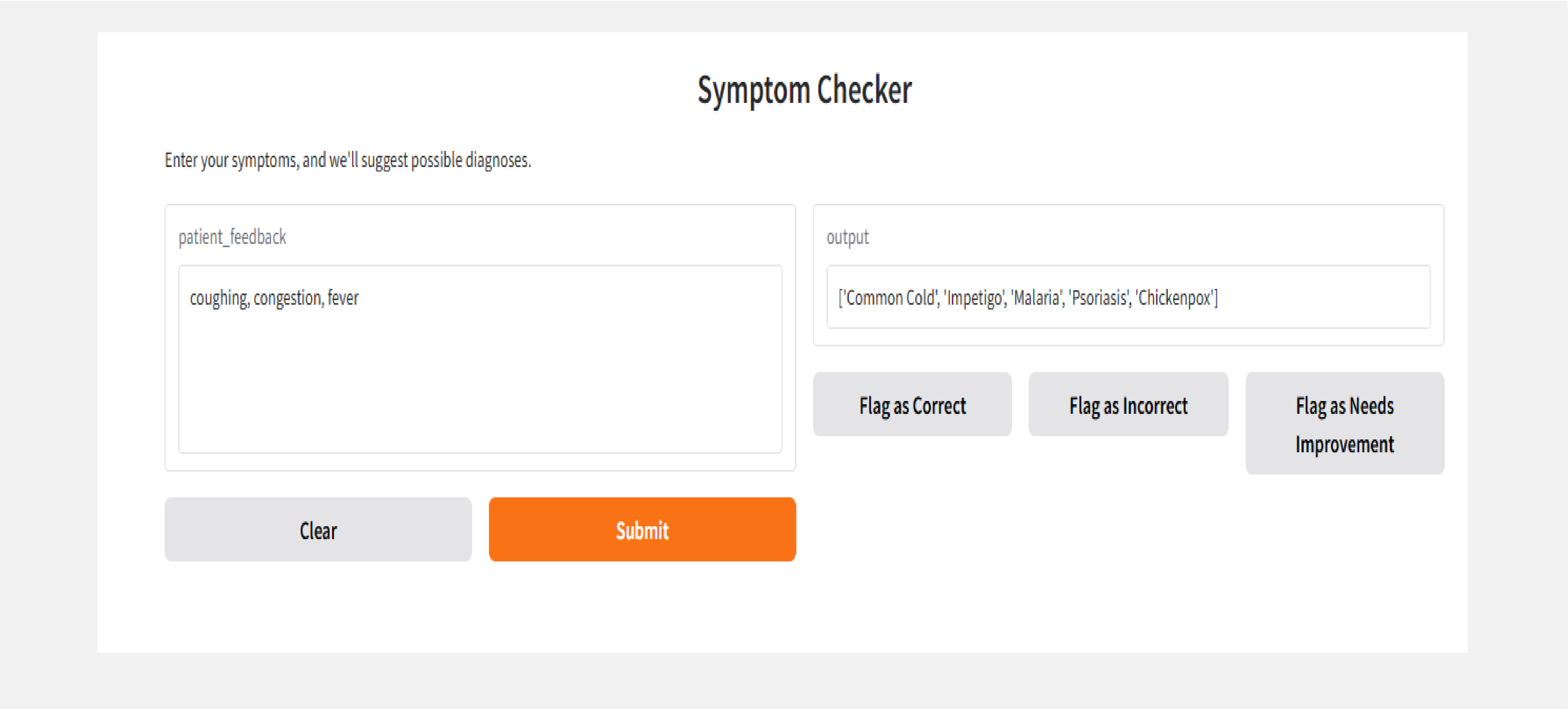
Disease Prediction Application

Our application allows for patients to input some symptoms into a symptom tracker. This information is then associated with some possible diagnoses.

Some new technologies we used (we did not cover in our boot camp) are:

1. **SentencePiece** which is a supplement to our NLTK. This supplement is needed to assist in translating medical terms or more complex words.
2. **%%capture** which is unique to Google Colab. This allows for the !pip installs to run without generating all the responses, which clutter up the application.
3. **sqlite** which is a lightweight database management system. Given that we are dealing with large dataset(s) for our model, sqlite allows our application to store and retreive data using SQL (structured query language.) We are using this for efficiency and speed of use.
4. **Flagging** we added this feature to our gradio interface. It is used to collect information from users about how the application is working. It is part of improving the model over time.

Disease Prediction Application



Disease Prediction Application
Output from our ‘flagging’ tool built into Gradio

Files

..
custom_flagged_data
dataset1.csv
sample_data
symbipredict.csv

dataset1.csv X

1 to 10 of 11 entries Filter

patient_feedback	output	flag	timestamp
skin rash, itching, swelling	['Chickenpox', 'Jaundice', 'Chronic Cholestasis', 'Hepatitis B', 'Drug Reaction']	Needs Improvement	2025-02-11 00:03:18.063648
skin rash, itching, swelling	['Chickenpox', 'Jaundice', 'Chronic Cholestasis', 'Hepatitis B', 'Drug Reaction']	Needs Improvement	2025-02-11 00:06:35.291604
congestion, fever, nausea, vomiting	['Common Cold', 'Hepatitis D', 'Hepatitis A', 'Dengue', 'Hepatitis E']	Needs Improvement	2025-02-11 00:07:06.364648
congestion, fever, nausea, vomiting	['Common Cold', 'Hepatitis D', 'Hepatitis A', 'Dengue', 'Hepatitis E']	Correct	2025-02-11 00:07:45.178327
rash, itching, swelling,	['Chickenpox', 'Jaundice', 'Chronic Cholestasis', 'Hepatitis B', 'Drug Reaction']	Correct	2025-02-11 00:08:09.806250
rash, itching, swelling, sneezing, skin irritation,	['Chickenpox', 'Jaundice', 'Chronic Cholestasis', 'Hepatitis B', 'Drug Reaction']	Incorrect	2025-02-11 00:10:48.157823
coughing, sneezing, headache, congestion	['Common Cold', 'Dengue', 'Chickenpox', 'Typhoid', 'Malaria']	Needs Improvement	2025-02-11 00:14:37.820036
congestion, coughing, fever, headache,	['Common Cold', 'Dengue', 'Chickenpox', 'Typhoid', 'Malaria']	Incorrect	2025-02-11 00:15:06.861320
nausea, vomiting, fever, headache,	['Dengue', 'Typhoid', 'Malaria', 'Hypoglycemia', 'Vertigo']	Incorrect	2025-02-11 00:21:41.612551
skin rash, itching, redness, swelling	['Chickenpox', 'Jaundice', 'Chronic Cholestasis', 'Hepatitis B', 'Drug Reaction']	Needs Improvement	2025-02-11 00:22:16.215378

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Challenges Encountered

1. SpaCy and Gradio had version conflicts, so Transformers (vectorizing) via TF-IDF was used for app development.

2. App was running too slow, so sqlite was used—it allows for data storage and retrieval using SQL for speed and efficiency

Summary

- ➔ A reliable dataset, the Symptom-Disease Prediction Dataset (SDPD) was used to train and evaluate multiple predictive algorithms.
- ➔ CNN outperformed other models, so was selected for integration into the Gradio app pilot.
- ➔ The **Gradio web app** pilot serves as a **testing interface** for users to input symptoms and receive **real-time disease predictions.**

Future Considerations

💡

Future Enhancements Post-Pilot

After piloting, improvements can be made based on user feedback and pilot results. Potential enhancements include:

🔷 **Enhancing Model Generalization** – Expanding the training dataset with more symptom-disease pairs.

🔷 **Improving Explainability** – Using SHAP or LIME to provide reasons behind predictions.

🔷 **API Integration** – Connecting with external health databases for supplementary information.

🔷 **Deployment on Cloud & Mobile** – Making the app available via cloud services and mobile applications.

Future Considerations

FUTURE FORWARD Health AI CONSIDERATIONS:

1. **Ethical, inclusive AI Models**: Bias-resistant diagnoses, culturally adapted AI, fair, affordable AI-based care such as **virtual health screenings** to underserved, rural populations, preventing healthcare disparities

2. **Environmental/social sustainability metrics**: health equity metrics, community and public health-centered AI models and apps

3. **Blockchain and decentralized health records**: smart contracts, fraud prevention, verification, patient control of own health records

4. **Real-time and Dynamic Health scoring**: AI-driven early warning systems, dynamic risk profiling, automated triage, prioritization in ERs

5. **Emerging / Alternative Health Data Sources**: Wearable devices, personalized medicine, DNA sequencing

6. **Network-based Health-Risk modeling**: community-based predictions, symptom tracking, public health policy

7. **Hybrid models**: Traditional rules + AI-based probabilistic models

Future Considerations

FUTURE FORWARD HEALTH AI CHALLENGES:

Key Challenges to Address:

•**Data Privacy and Security**: HIPPA, EHRs, more

•**Secure AI Model Training**: Preventing AI-powered cyber threats

•**Regulatory Compliance**: Aligning innovations with HHS, FDA, CDC, more

•**User Trust**: Building confidence in AI-powered healthcare

•**Fairness and Bias Mitigation**: Diverse and Representative Data

•Tackling these challenges is crucial to **unlock the full potential of AI in healthcare**.

• **AI-powered healthcare** has the potential to enhance patient outcomes, improve accessibility, and revolutionize modern medicine.