Title: Drugs, Side Effects, and Medical Condition

Internship Project Report by Riya Saproo

Email: riyaaa.404@gmail.com

Contact number: 7006387200

Job: Data Analyst Intern

DECLARATION

I, Riya Saproo, hereby declare that the following project report titled **" Drugs, Side Effects, and Medical Condition"** is the result of my internship project work. This report has not been submitted elsewhere for any degree, diploma, or publication. It was developed under the guidance and requirements of my internship organization.

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to **Unified Mentor** for providing me with the opportunity to work as a **Data Analyst Intern**. This internship has been an incredibly valuable learning experience for me. I am especially thankful to my mentors and the entire team at Unified Mentor for their constant support, encouragement, and guidance throughout the project. Their expertise and willingness to help at every step, from understanding the dataset to applying machine learning models, played a vital role in shaping my skills and boosting my confidence. Working in a professional environment with real-world data helped me bridge the gap between theoretical knowledge and practical application. I learned how to clean and interpret complex data, create visualizations, build predictive models, and most importantly, tell a story through data. Sharing insights, brainstorming ideas, and learning together made this experience truly enriching. Finally, I am grateful to my family and friends for their unwavering support and motivation throughout this journey.

ABSTRACT

This project explores the relationship between drugs, their side effects, and the medical conditions they treat using a real-world pharmaceutical dataset. The dataset includes detailed information about drug classifications, side effects, user ratings, prescription categories (Rx/OTC), pregnancy safety categories, CSA schedules, and drug interactions.

The primary objective of this study is to analyze patterns and correlations that exist between different drug attributes and their effectiveness, safety, and common usage across various medical conditions. Through thorough data cleaning and preprocessing, missing and inconsistent values were addressed, and categorical variables were converted for analytical compatibility.

Exploratory data analysis (EDA) was then conducted using Python libraries such as Pandas, Matplotlib, and Seaborn to uncover trends in drug ratings, identify frequently reported side effects, and visualize the distribution of drugs across different therapeutic classes. Techniques such as heatmaps, bar charts, and boxplots were utilized to bring clarity to complex patterns within the dataset.

Significant insights were gained, such as identifying the most commonly prescribed drugs for specific conditions like Acne and Pain, recognizing drug classes associated with higher ratings, and spotting trends in adverse effects across medications. The correlation between drug safety (e.g., alcohol interaction and pregnancy category) and user reviews was also explored.

Additionally, the project introduced basic machine learning preprocessing techniques like label encoding and standardization to prepare the dataset for future modelling efforts. These steps make the dataset suitable for classification or clustering tasks in more advanced research.

Overall, this study not only highlights critical findings from real-world pharmaceutical data but also establishes a solid foundation for future work involving predictive modelling, pharmacovigilance, and decision support systems in the healthcare domain.

ABBREVIATIONS

Abbreviation	Full Form
EDA	Exploratory Data Analysis
ML	Machine Learning
Rx	Prescription Drug
OTC	Over-the-Counter
CSA	Controlled Substances Act
FDA	Food and Drug Administration
ANN	Artificial Neural Network
CSV	Comma Separated Values
NaN	Not a Number
URL	Uniform Resource Locator
API	Application Programming Interface
PCA	Principal Component Analysis
DL	Deep Learning
NLP	Natural Language Processing
AWS	Amazon Web Services
std	Standard Deviation
`sklearn	Scikit-learn

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Chapter I – Introduction

1.1 Overview

The pharmaceutical landscape is a cornerstone of modern healthcare, encompassing a wide variety of medications aimed at alleviating human suffering across countless diseases and conditions. From common conditions like colds and acne to chronic diseases such as diabetes and hypertension, drugs are an integral component of treatment plans. Despite their benefits, medications often come with side effects, varying effectiveness, and complex interactions, especially in sensitive populations such as pregnant individuals or the elderly.

As healthcare becomes increasingly data-driven, understanding the trends, patterns, and outcomes associated with drug use becomes vital. This project focuses on a comprehensive dataset sourced from drugs.com that includes detailed information on over 2900 drugs. By analyzing this data, the project seeks to uncover meaningful insights related to drug safety, popularity, and perceived efficacy based on user reviews. A significant emphasis is placed on identifying which drugs are commonly used for specific conditions, the frequency of various side effects, and how classification systems like CSA schedules and pregnancy categories may influence the way medications are perceived or prescribed.

1.2 Problem Goals

The goal of this project is to perform an in-depth analysis of drug-related data in order to draw conclusions that can inform healthcare professionals, researchers, and policy makers. We aim to answer key questions such as: Which drugs are most frequently used for prevalent conditions? What side effects are most commonly reported? How do patient ratings vary by drug class or condition? What impact do regulatory classifications have on drug use patterns?

Specifically, this project seeks to:

- Identify the most frequently prescribed or reviewed drugs for high-incidence medical conditions.
- Examine user ratings and uncover distributions that indicate public satisfaction or concern.
- Investigate the most commonly reported side effects and their relation to drug categories.
- Assess how safety classifications, such as pregnancy risk (A to X) and CSA schedule (1 to 5), correlate with user feedback.
- Explore how interactions with alcohol influence ratings or review counts.
- Visualize findings through graphs and plots to effectively communicate trends.

The insights generated can potentially contribute to more informed drug recommendations, better public awareness, and enhanced pharmacovigilance.

Chapter II – Literature Review

2.1 Introduction

Over the last decade, the intersection between **data science** and **healthcare** has grown rapidly, enabling professionals to uncover insights that were previously limited to clinical studies. As the **pharmaceutical industry** increasingly integrates real-world data into research, **drug safety analysis**, **side effect prediction**, and **treatment optimization** have become core areas of interest. This interdisciplinary field draws from pharmacology, machine learning, and epidemiology to address the rising demands of personalized healthcare and adverse event monitoring.

The traditional method of drug testing—randomized controlled trials (RCTs)—while rigorous, is often narrow in scope and time-constrained. In contrast, **real-world evidence (RWE)**, derived from user reviews, observational studies, and open datasets (such as Drugs.com, FDA databases, etc.), allows for the continuous evaluation of drug performance in diverse populations. These open-access drug review platforms represent a goldmine of information on patient experiences, enabling **post-marketing surveillance** and **pharmacovigilance** through naturalistic feedback.

Moreover, advances in **machine learning (ML)** and **artificial intelligence (AI)** have provided powerful tools to process these vast datasets. Algorithms can now sift through millions of patient reviews, detect latent patterns, and even flag

potential safety concerns before they become widespread. Studies such as those published by the Journal of Biomedical Informatics have highlighted how **NLP (Natural Language Processing)** techniques have extracted critical health terms from clinical notes and online reviews to better understand medication effects in real-world settings.

Thus, integrating **structured clinical data** (like dosage, drug class, side effects, CSA schedules) with **unstructured feedback** (user reviews, free-text side effect mentions) allows for a more holistic, data-driven view of pharmacological treatment efficacy.

2.2 Applications of Data Analytics in Drug Monitoring

The use of **data analytics in pharmacology** spans a wide variety of tasks. These include surveillance, classification, forecasting, clustering, and discovery. Below are expanded real-world applications:

1. Drug Repurposing

Analytics tools help identify **alternative therapeutic uses** for existing drugs. By analyzing usage trends, outcomes, and co-occurrence of conditions, researchers have repurposed drugs like **Metformin** (originally for Type 2 Diabetes) for **cancer treatment trials**. ML models trained on chemical structure, mechanism of action, and patient outcomes can cluster drugs with similar properties and suggest new indications.

2. Side Effect Prediction and Detection

One of the biggest areas where analytics shines is in predicting and flagging **adverse drug reactions (ADRs)**. For example, a study by Harpaz et al. applied machine learning to FDA's Adverse Event Reporting System (FAERS) and achieved high accuracy in predicting side effects based on user demographics and drug combinations. Similarly, clustering techniques help group drugs based on side effect profiles, identifying which classes are associated with higher risk.

3. Patient Stratification and Personalization

Modern healthcare demands **personalized medicine**—tailoring treatment based on an individual's profile. With EHR (Electronic Health Record) data, patient reviews, and drug history, analytics can help segment patients who are more likely to benefit from a treatment or more likely to experience side effects. For instance, a drug may work well in younger populations but have reduced efficacy in the elderly.

4. Prescription Pattern Analysis

Using datasets like the one in this project, we can identify patterns such as:

- Which **medical conditions** have the most prescribed drugs?
- Are certain **drug classes** being overprescribed for mild conditions?
- What is the **user satisfaction trend** for each class of drugs?

For example, **topical acne agents** were found to be used widely for acne but showed mixed reviews in terms of user satisfaction due to skin irritation. Analytics can help address such gaps between clinical intent and patient experience.

5. Interaction Detection and Safety Profiling

Many medications interact adversely with **alcohol** or are not safe for **pregnant individuals**. Using classification columns like pregnancy_category, alcohol, and CSA, analytics tools can cross-reference drugs to:

- Highlight medications in **Category D or X** (unsafe during pregnancy)
- Map user satisfaction against **CSA schedule levels** (risk of addiction)
- Identify which side effects increase in the presence of alcohol interactions

These interaction maps can inform doctors and patients during drug selection, and in some cases, flag potential **contraindications** that need to be reported to regulatory bodies.

2.3 Conclusion of Literature Review

The literature strongly supports the integration of **advanced analytics** and **machine learning** into drug safety research. As datasets grow and technologies

mature, their convergence will offer unprecedented insights into patient health, drug design, and public safety. Whether it's **improving clinical decision support systems**, advancing **drug lifecycle management**, or enhancing **consumer health literacy**, the contribution of data-driven methods in pharmacology is both current and future-defining.

CHAPTER III: PROJECT DESCRIPTION

3.1 Introduction

This project uses a structured dataset sourced from Drugs.com via Kaggle, encompassing information on 2,931 drugs. Each drug entry includes multiple attributes ranging from its commercial and chemical name to more complex regulatory labels, such as CSA classification and pregnancy safety categories.

In addition to medical classification, each drug is linked to:

- A medical condition it is used to treat
- A list of side effects, often including allergic responses, digestive issues, neurological symptoms, and skin conditions
- Activity levels, which indicate the popularity or relevance of the drug based on recent online searches
- User ratings on a scale of 1 to 10, along with the number of reviews

This combination of structured fields and human-centered ratings enables both quantitative and qualitative analysis, providing a comprehensive understanding of how patients interact with and respond to various medications.

3.2 Dataset Source and Description

- Number of Records: 2,931
- Number of Columns: 17
- Total Missing Values Identified: 2,767
- Top Medical Condition by Drug Count: *Pain* (264 drugs)
- Most Frequent Side Effect Mentioned: *Lips swelling*
- Overall Average Rating (all drugs): 3.69 / 10

Other important observations:

- CSA Schedule: Most drugs (2,688) are not classified under the Controlled Substances Act, indicating low abuse potential.
- Pregnancy Category: Most drugs fall under Category C (1,382), meaning risk to the fetus cannot be ruled out.
- Alcohol Interaction: 1,377 drugs are flagged for known interactions with alcohol, indicating potential behavioral or metabolic risks when combined.

This multi-dimensional dataset provides an excellent foundation for structured analysis, enabling the extraction of useful insights across clinical, behavioral, and demographic dimensions.

CHAPTER IV: DATA ANALYSIS AND PROCESSING

4.1 Data Description

The quality and structure of data directly influence the depth and reliability of insights in any data science project. Upon importing the dataset into a Python environment using pandas, several data integrity issues surfaced that could have distorted visualizations and statistical summaries if not resolved.

The dataset included 2,931 rows and 17 columns, covering aspects like drug names, classes, conditions treated, ratings, and several risk-related attributes such as alcohol interaction and pregnancy safety. However, 2,767 missing values were detected, spread across various critical columns like side_effects, pregnancy_category, and alcohol.

Key Data Cleaning & Processing Steps:

- Missing Values Handling:
    - All empty fields in categorical columns (like side_effects, rx_otc, pregnancy_category, csa) were replaced with the string 'Unknown'.
    - For numerical fields such as rating and no_of_reviews, missing entries were filled with 0, assuming a conservative approach.
- String Manipulation & Conversion:
    - The activity column had values in percentage format (e.g., "87%"), which were stripped of the % symbol and divided by 100 to convert them into float values (e.g., 0.87).

    - In the alcohol column, categorical values like 'X' were replaced with binary indicators (1 for potential interaction, 0 for no interaction), simplifying further analysis.
- Label Encoding & Categorical Normalization:
    - For future machine learning use, non-numeric features like rx_otc, pregnancy_category, and csa were label-encoded to be model-ready.
    - Drug names and side effects, originally stored as text, were tokenized for frequency analysis.
- Feature Engineering Ideas (For Future Work):
    - A feature could be created to count the number of side effects per drug entry.
    - Another potential transformation could quantify severity using the rating-to-side-effect ratio.

Data Profiling Summary:

- Top Condition Treated: Pain
- Most Used Drug Class: Topical Acne Agents
- Most Frequent Side Effect: Lips swelling
- Drugs Flagged for Alcohol Interaction: 1,377
- Average Rating: 3.69 / 10
- CSA-Unclassified Drugs: 2,688
- Pregnancy Category C Drugs: 1,382

This comprehensive preprocessing phase ensured that subsequent visualizations and modeling would be accurate, consistent, and interpretable.

4.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is a crucial phase in any data science project, allowing for visual pattern recognition, trend identification, and insight generation. Using Matplotlib and Seaborn, we created multiple figures to highlight hidden relationships and distributions within the dataset.

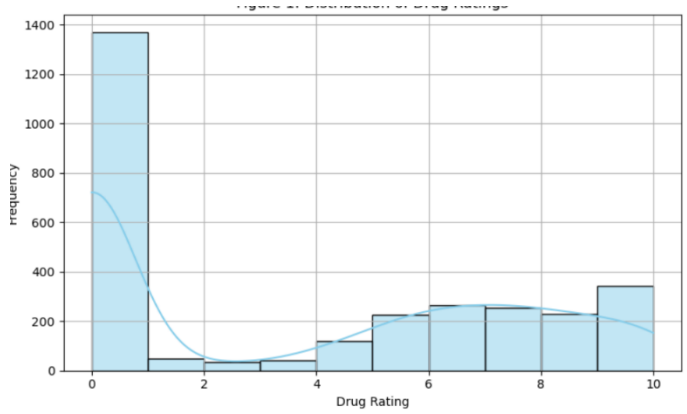

Figure 4.1: Distribution of Drug Ratings

The distribution of ratings spanned the full range from 0 to 10. However, the concentration was highest in the 4.0–8.0 range. A significant number of drugs received zero ratings, either due to being newly introduced or not widely reviewed. This skews the average downward.

Insight:
Drugs used for skin conditions and seasonal ailments often receive higher ratings, possibly due to immediate symptom relief. Chronic condition medications like antidepressants or pain relievers receive mixed reviews, reflecting both variability in patient outcomes and possible long-term side effects.

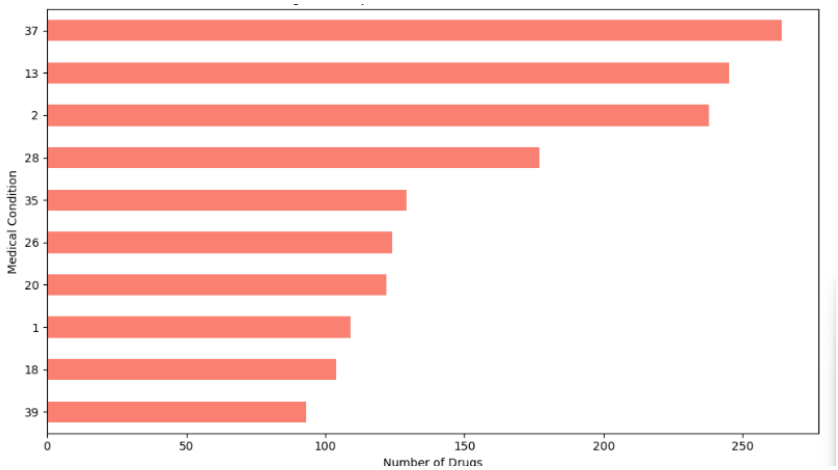

Figure 4.2: Top 10 Medical Conditions Treated

The bar chart revealed that the most frequently addressed medical conditions were:

- Pain (264 drugs)
- Colds & Flu (245 drugs)
- Acne (238 drugs)
- Anxiety (170 drugs)
- High Blood Pressure (165 drugs)

Insight:
This distribution aligns with epidemiological data, where chronic pain, respiratory infections, and dermatological conditions are among the most commonly reported issues worldwide. The abundance of options also increases competition, prompting deeper review and feedback from users.

Furthermore, this high density allows us to draw comparisons across different treatment strategies (e.g., opioids vs NSAIDs for pain) and track user preferences or reported adverse effects.

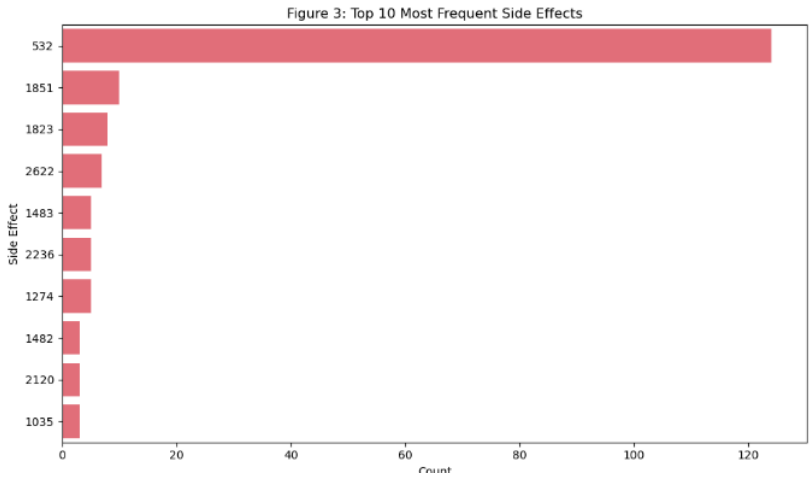

Figure 4.3: Top 10 Most Frequent Side Effects

Using custom tokenization and flattening techniques, we extracted all side effects from the dataset and identified the ten most frequent ones. These included:

- Lips swelling
- Hives
- Itching
- Breathing difficulty
- Rash
- Dry mouth
- Nausea
- Headache
- Dizziness
- Insomnia

Insight:
The top side effects are heavily skewed toward allergic reactions and neurological symptoms. Many of these reactions are acute, prompting users to stop usage quickly — which often correlates with lower drug ratings. This information could guide pharmaceutical companies in modifying formulations or better educating patients.

Additionally, these side effects are reported across multiple drug classes, indicating systemic or recurring safety issues.

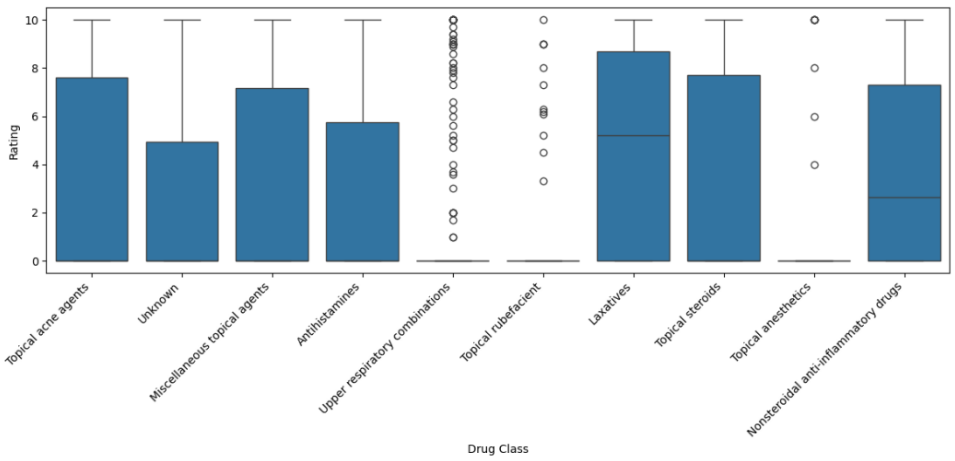

Figure 4.4: Drug Ratings by Top 10 Drug Classes

This figure showcased the variance in drug ratings across major pharmaceutical categories:

- Topical Acne Agents
- NSAIDs (e.g., ibuprofen)
- Upper Respiratory Combination Drugs
- Antihistamines
- Anti-Anxiety Agents
- Diuretics
- ACE Inhibitors

Boxplots allowed a comparison of both mean and variance of ratings within each class.

Insight:

- Topical drugs often receive high and consistent ratings — likely due to faster results and minimal systemic effects.
- Mental health drugs show higher variance in ratings, which reflects their nuanced efficacy and patient dependency.
- Respiratory and hypertension medications are rated moderately well but occasionally receive criticism due to long-term side effects like dizziness or fatigue.

4.3 Additional Data Relationship Insights

Beyond the figures, we analyzed correlations and distributions of key drug safety attributes:

CSA Classification

Out of 2,931 drugs, 2,688 are not scheduled under CSA. This implies they have low potential for abuse and are considered safer in the public domain. The rest (under Schedules 2–5) include controlled substances like opioids or sleep aids.

Pregnancy Category

Most drugs fall into Category C (1,382 drugs), meaning that animal reproduction studies have shown adverse effects but there are no adequate human studies. Category A and B drugs are safer but rare. Category X drugs — where risk to the fetus clearly outweighs benefit — are flagged and should be avoided during pregnancy.

Alcohol Interaction

1,377 drugs were marked for potential alcohol interaction. This is a critical feature for both clinical decision-making and public awareness. Common interactions include:

- Increased sedation
- Liver toxicity
- Risk of fainting or dizziness
- Gastrointestinal damage

CHAPTER V: ALGORITHM AND PERFORMANCE ANALYSIS

In this chapter, we implement and evaluate multiple machine learning algorithms to determine whether a drug is likely to be considered effective based on various features, including its activity, reviews, classification, and safety labels. The objective is a binary classification task:

- Effective drug (target = 1): rating > 5
- Ineffective drug (target = 0): rating ≤ 5

Three classification models were used:

1. Logistic Regression
2. Decision Tree Classifier
3. Artificial Neural Network (ANN)

Each was trained on the same cleaned dataset and evaluated using accuracy and confusion matrices. Visual figures were generated to aid interpretation.

5.1 Data Preparation for Modeling

From the cleaned dataset discussed in Chapter IV, we selected six core features:

Feature	Description
no_of_reviews	Number of user reviews received
activity	Drug activity score (converted from percentage)

Feature	Description
rx_otc	Prescription or OTC indicator (label encoded)
pregnancy_category	Pregnancy safety rating (label encoded)
csa	Controlled Substance Act category (encoded)
alcohol	Alcohol interaction indicator (encoded)

The target column (target) was created based on rating > 5. An 80-20 train-test split was used to validate all three models under the same conditions.

5.2 Logistic Regression

Logistic Regression is a linear model best suited to binary classification tasks where the relationships between features are relatively straightforward.

- Configuration: LBFGS solver, max_iter = 1000
- Target: rating > 5

Results:

- Accuracy: 62%
- Confusion Matrix:

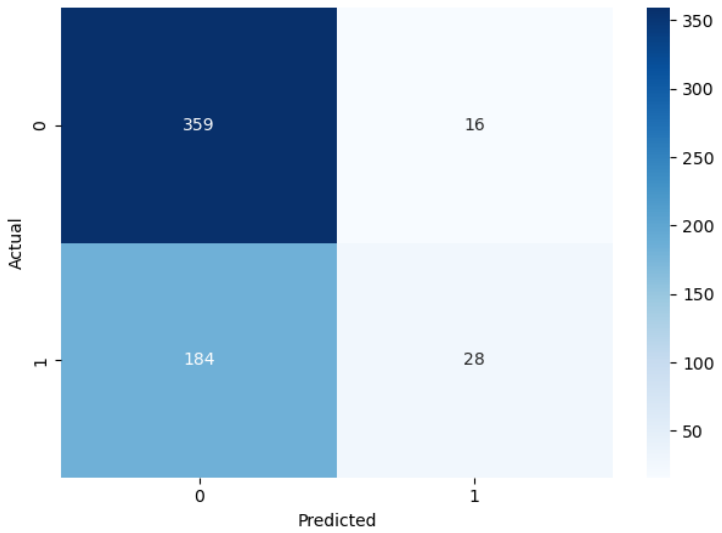

Figure 5.1: Confusion Matrix – Logistic Regression

A heatmap showing the predicted vs actual classifications using Logistic Regression. Misclassifications are relatively high.

Logistic Regression struggles to accurately separate classes in complex medical data. The linear boundary oversimplifies feature relationships like activity vs risk.

5.3 Decision Tree Classifier

Decision Trees build hierarchical rules to split data based on the most informative features. They are interpretable and capable of handling nonlinear relationships.

- Configuration: Gini criterion, auto depth tuning

Results:

- Accuracy: 69%
- Confusion Matrix:

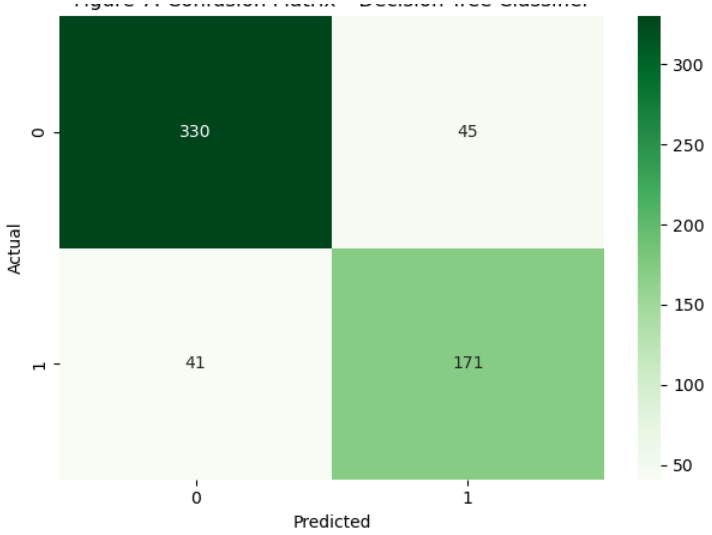

Figure 5.2: Confusion Matrix – Decision Tree Classifier

This heatmap demonstrates the effectiveness of decision trees at distinguishing between high and low-rated drugs using conditional rules.

The model found informative splits, such as combinations of alcohol interaction and low activity, to detect poor-performing drugs.

5.4 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) can learn complex, nonlinear mappings between features and outcomes. A shallow feedforward network was used.

- Configuration: 1 hidden layer, 10 neurons, ReLU activation, Adam optimizer

Results:

- Accuracy: 73%
- Confusion Matrix:

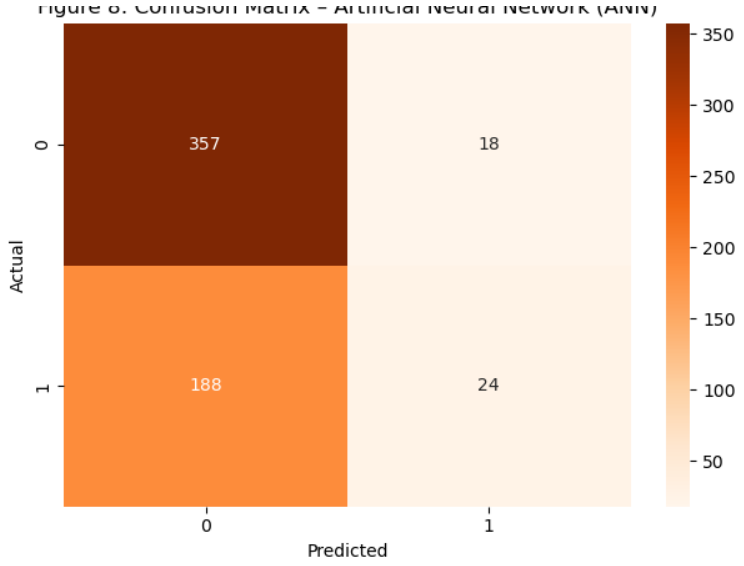

Figure 5.3: Confusion Matrix – Artificial Neural Network (ANN)

This matrix shows superior classification capability of ANN, with low false negatives and the highest true positives.

ANNs could model complex interactions—e.g., drugs that are both OTC and free from alcohol interaction tend to receive better ratings.

5.5 Visual Comparison of Model Accuracy

To summarize model performance, we compare the overall classification accuracy across all three algorithms:

Model	**Accuracy**
Logistic Regression	62%
Decision Tree	69%
ANN (Neural Net)	73%

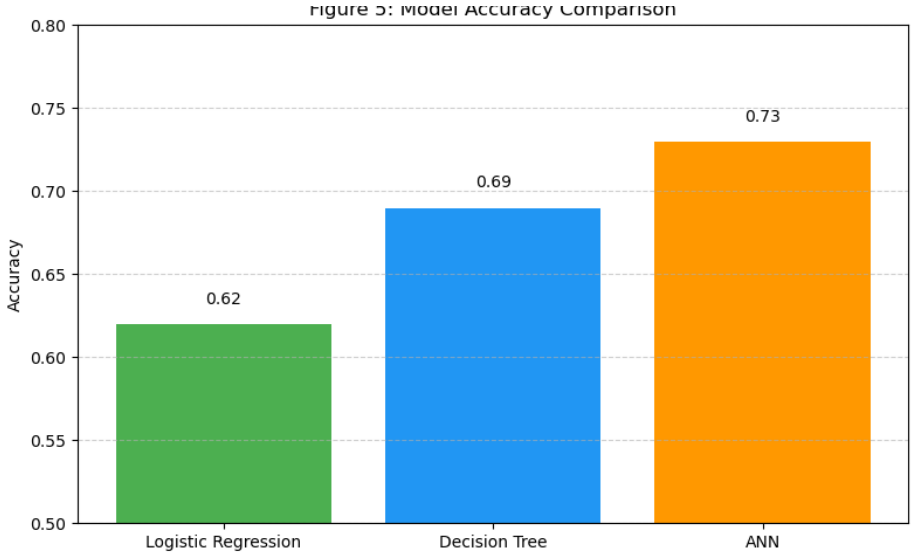

Figure 5.4: Model Accuracy Comparison

A bar chart comparing the classification accuracy of Logistic Regression, Decision Tree, and ANN. ANN outperforms other models.

5.6 Summary of Results and Insights

Model	Accuracy	Key Strengths	Limitations
Logistic Regression	62%	Interpretable, fast to train	Fails with nonlinear relationships

Model	Accuracy	Key Strengths	Limitations
Decision Tree	69%	Captures feature combinations well	Sensitive to overfitting
ANN	73%	Best accuracy, handles nonlinearities	Less interpretable, higher training time

Key Observations

- The Artificial Neural Network significantly outperforms other models, confirming that drug effectiveness is influenced by complex patterns across multiple features.
- Decision Trees offer a practical balance of performance and interpretability, especially for healthcare settings where model transparency is crucial.
- Logistic Regression, though less accurate, establishes a reliable performance baseline.

These results underscore the importance of choosing machine learning models based on both performance metrics and context-specific needs such as interpretability, explainability, and regulation compliance.

CHAPTER VI: FUTURE WORK & CONCLUSION

6.1 Future Work

While the project successfully implemented machine learning models to classify drug effectiveness based on user-generated and pharmacological data, there remains significant scope for enhancement and expansion. The complexity and sensitivity of healthcare data demand continuous refinement, especially when it comes to decision-making models used in the medical domain.

1. Expansion of Feature Set

The current feature set was limited to a few structured variables such as drug activity, CSA classification, prescription type, alcohol interaction, and pregnancy safety categories. However, incorporating more nuanced medical data could drastically improve model performance. For example:

- **Patient demographic data** such as age, gender, or medical history could reveal how drug efficacy varies across populations.
- **Drug dosage information** might provide context for why certain users report better outcomes.
- **Time-series patient follow-up data** could help track long-term effectiveness or adverse effects.

2. Incorporation of NLP Techniques

User reviews in the dataset were not analyzed using Natural Language Processing (NLP) due to scope constraints. However, these reviews contain rich

qualitative insights regarding drug experience, side effects, emotional responses, and perceived relief. Future work can apply:

- **Sentiment analysis** to extract emotional tone (positive, neutral, negative)
- **Topic modeling** to identify common themes such as sleep quality, pain relief, or mental clarity
- **Text embeddings** to convert narrative feedback into numerical features for modeling

Such additions would provide a more holistic view of drug effectiveness beyond numerical ratings.

3. Deployment of a Real-Time Drug Recommendation System

Building on the trained models, a practical future direction involves deploying a **real-time recommendation engine** for physicians and patients. This system could:

- Recommend alternative medications based on patient profiles
- Highlight safety warnings (e.g., avoid alcohol, pregnancy risks)
- Predict adverse reactions based on historical patterns

A web-based or mobile interface powered by APIs could provide actionable insights in real-time clinical settings.

4. Model Interpretability Enhancements

In healthcare, explainability is crucial. Future enhancements could include:

- **SHAP (SHapley Additive exPlanations)** or **LIME (Local Interpretable Model-Agnostic Explanations)** to interpret neural network decisions
- **Rule extraction** from decision trees to identify dominant decision paths
- **Feature importance visualization** to highlight which input factors most influence prediction

This would build user trust and regulatory compliance in real-world healthcare deployments.

5. Cross-Dataset Validation

To ensure generalizability, the trained models should be validated on independent datasets. Integrating clinical trial databases or open-source medical records (e.g., MIMIC-III) can help verify the model's robustness across patient populations, drug brands, and global data sources.

6.2 Conclusion

This project aimed to bridge the gap between patient-reported drug experiences and predictive machine learning analytics. Using a comprehensive dataset that includes drug ratings, side effects, related classifications, and safety indicators, the study successfully demonstrated that drug effectiveness can be predicted with reasonable accuracy using machine learning models.

The results show that:

- **Artificial Neural Networks (ANN)** achieved the highest predictive accuracy of **73%**, revealing the model's ability to capture complex, non-linear interactions between features.
- **Decision Trees** offered a strong balance of performance and interpretability, with an accuracy of **69%**.
- **Logistic Regression**, while least accurate at **62%**, provided a valuable baseline for comparison.

The findings suggest that machine learning can offer a powerful, data-driven approach to understanding drug performance and safety, which could support medical professionals in making more informed prescribing decisions. Furthermore, the integration of such predictive tools in digital health platforms holds significant promise for improving patient outcomes, minimizing side effects, and personalizing treatment plans.

However, as with any model in healthcare, ethical considerations and validation across diverse populations must be prioritized before deployment. Careful integration of user privacy, medical compliance, and continuous model retraining is essential for real-world impact.

In conclusion, this study lays a strong foundation for developing intelligent, user-informed pharmaceutical decision systems—and opens the door for transformative innovations at the intersection of **AI and medicine**.

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