STARTUP ALCHEMY:

Turning Data into Success Spells

PROJECT REPORT

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TABLE OF CONTENTS

1. ACKNOWLEDGEMENTS

With immense pleasure, we, **Ayush Bansal, Manya Saini** and **Virender Garg** are presenting the “**STARTUP ALCHEMY: Turning Data into Success Spells**” project report as a part of the curriculum of ‘BE-CSE(AI)’.

We would like to express our sincere thanks to “**Dr. Kanika**” and “**Dr. Tanvi Sood**”, for their valuable guidance and support in completing our project.

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2. ABSTRACT

In response to the dynamic and ever-evolving landscape of startups, there is an increasing need for innovative approaches that can accurately predict success and provide strategic guidance. Our project, titled "Startup Alchemy: Turning Data into Success Spells," represents a concerted effort to harness the synergies between data and artificial intelligence (AI) to forecast the success of startups. With a special emphasis on the vibrant domain of AI startups in healthcare, we embark on a multifaceted journey. Through the concurrent training of three distinct models and the adept use of advanced visualization techniques, our project aspires to furnish stakeholders with a comprehensive and nuanced understanding of the myriad factors that influence startup success.

At its core, our project revolves around the meticulous curation of a tailored dataset, meticulously capturing pivotal features that wield significant influence over the trajectory of startups. Employing sophisticated machine learning models for predictive analytics, we delve into the dataset to unravel intricate patterns and discern the hidden determinants of startup success. The outcomes of these models undergo not only robust analytical scrutiny but also find expression through compelling visualizations crafted using the powerful Matplotlib library in Python. This synergistic approach ensures a holistic interpretation of results, effectively demystifying the complexities inherent in the landscape of startup success.

As we navigate through the intricacies of the startup ecosystem, our project seeks to empower entrepreneurs, investors, and decision-makers with actionable insights. These insights, derived from cutting-edge AI and data analytics, are poised to act as compasses, guiding stakeholders in shaping the future trajectory of AI startups in healthcare. The subsequent sections of this report will delve into the methodologies, results, and implications of our project, providing a comprehensive roadmap for stakeholders seeking to navigate the dynamic and often unpredictable terrain of startup success.

3. LIST OF FIGURES

4.1 INTRODUCTION

In a landscape characterized by innovation, risk, and transformative potential, the success of startups remains a pursuit that intrigues and challenges stakeholders across industries. "Startup Alchemy" represents our endeavor to unravel the complexities of startup success prediction, a task made even more intricate when applied to the specialized domain of AI startups in healthcare.

Dataset Creation and Model Training: At the core of our project is the creation of a bespoke dataset, meticulously curated to encapsulate crucial features that influence startup success. We leverage machine learning, employing three simultaneous models – Gradient Boosting, Random Forest, and Decision Tree – to unravel patterns and correlations within this data. The distinctiveness of our approach lies in its applicability to AI startups in healthcare, a sector that demands a specialized lens.

Visualization for Comprehensive Interpretation: To ensure the accessibility and interpretability of our predictive models, we turn to advanced visualization techniques. Platforms like Matplotlib in Python serve as our canvas, enabling stakeholders to comprehend and explore the outcomes comprehensively. The visual representation of our findings is instrumental in translating complex machine learning outcomes into actionable insights.

Focus on AI Startups in Healthcare: Recognizing the dynamic nature of the healthcare industry and the transformative potential of AI, our project narrows its focus to startups operating at this intersection. By doing so, we acknowledge the unique challenges and opportunities that define success in this niche, tailoring our predictive models to the specific demands of the healthcare landscape.

Through "Startup Alchemy," we aim to empower decision-makers with a tool that transcends traditional predictive models, offering a nuanced understanding of success factors in the realm of AI startups in healthcare. The subsequent sections delve into the methodologies, results, and implications of our project, outlining a roadmap for stakeholders to navigate the dynamic and often unpredictable terrain of startup success.

4.2 PROBLEM FORMULATION

In the ever-evolving landscape of startups, predicting success remains an elusive pursuit. The absence of a reliable and comprehensive predictive model hampers the ability of entrepreneurs, investors, and stakeholders to make informed decisions. Traditional methods often fall short in capturing the intricate dynamics that influence a startup's trajectory, particularly within the specialized domain of artificial intelligence (AI) startups in healthcare.

This project addresses the critical gap in predictive tools tailored for the unique challenges faced by AI startups in healthcare. The absence of a nuanced, multi-model approach limits the ability to discern patterns, correlations, and key factors that contribute to success in this specific niche. Without a comprehensive understanding of these factors, stakeholders risk making decisions based on incomplete information, leading to suboptimal outcomes.

The overarching problem, therefore, is the lack of a robust predictive framework that integrates advanced machine learning models and data visualization techniques to offer actionable insights into the success potential of AI startups in healthcare. "Startup Alchemy" seeks to bridge this gap, providing a solution that empowers stakeholders with a predictive tool tailored to the intricacies of the healthcare-focused AI startup ecosystem.

By formulating and implementing this innovative project, we aim to empower decision-makers with a reliable and interpretable solution, facilitating better strategic planning, investment decisions, and ultimately contributing to the success and sustainability of AI startups in the healthcare domain.

4.3 PROPOSED SOLUTION

The project encompasses a range of features designed to address the challenges faced by startup entrepreneurs. It provides a comprehensive solution tailored to overcome the complexities inherent in predicting the success of startups:

1. Research and Project Selection:

The inception of "Startup Alchemy: Turning Data into Success Spells" was grounded in a comprehensive exploration of the contemporary startup landscape. Extensive research identified the need for innovative approaches to predict startup success, particularly within the burgeoning field of AI startups in healthcare. The project aims to bridge the gap between data-driven insights and strategic decision-making.

Benefits:

- *Informed Decision-Making*: Enables stakeholders to make strategic decisions based on predictive analytics.
- *Targeted Focus*: Specifically addresses the challenges and opportunities within the AI startup ecosystem in healthcare.

2. Creating Bespoke Dataset

A critical foundation of our project lies in the creation of a bespoke dataset, meticulously curated to encapsulate the essential features influencing startup success. This process involves the extraction and compilation of relevant data points that are crucial for training robust machine learning models.

Benefits:

- *Tailored Insights*: The dataset is customized to capture nuances relevant to the success of startups.
- *Model Training*: Provides a robust foundation for training machine learning models.

3. Visualization for Selecting Factors

Leveraging the capabilities of Python's Matplotlib, our project employs a repertoire of sophisticated visualization techniques to discern and select key factors influencing startup success. The following visualization methods play a pivotal role in this exploratory process:

1. **Correlation Visualization**

Utilizing correlation matrices, we visually represent the relationships between different variables in the dataset. This technique enables a nuanced understanding of how factors coalesce or diverge, guiding the identification of correlated features.

Benefits:

- **In-Depth Correlation Analysis:** Provides a comprehensive view of inter-variable relationships.
- **Multivariate Insight:** Identifies patterns and dependencies among multiple factors.

2. **Sankey Plot**

The Sankey plot offers an intuitive and interactive way to visualize the flow of resources or, in our case, the impact of different factors on startup success. It helps unveil the intricate pathways that contribute to favorable or unfavorable outcomes.

Benefits:

- **Flow Visualization:** Illustrates the contribution and distribution of various factors.
- **Pathway Identification:** Highlights the predominant pathways influencing startup success

.

3. **Scatter Plot**

Scatter plots serve as a powerful tool for visualizing the relationship between two continuous variables. In our context, scatter plots aid in uncovering trends, clusters, or outliers, providing valuable insights into the distribution of influential features.

Benefits:

- **Variable Interaction:** Depicts how pairs of variables interact with each other.
- **Outlier Detection:** Identifies anomalies that might impact startup success predictions.

Benefits of Visualization Techniques:

- *Intuitive Exploration*:
    - The combination of correlation matrices, Sankey plots, and scatter plots offers an intuitive exploration of complex data relationships.
    - Stakeholders can interactively navigate visual representations for a deeper understanding.
- *Informed Feature Selection*:
    - Visualization serves as a guide in selecting influential features for model training.
    - Clear visualizations empower stakeholders to make informed decisions on the inclusion or exclusion of specific variables.

Incorporating these diverse visualization techniques ensures a robust and nuanced exploration of the dataset, enhancing the clarity and efficacy of feature selection for subsequent model training stages.

4. Dividing Dataset into Train and Test Data

The dataset is systematically divided into training and testing subsets, ensuring the models are trained on a representative sample and evaluated on an independent dataset. This step is crucial for assessing the generalization capabilities of the models.

Benefits:

- *Model Evaluation*: Enables the assessment of model performance on unseen data.
- *Generalization*: Enhances the ability of models to make accurate predictions on new startup data.

5. Training Three Models

Our project employs three distinct machine learning models—Gradient Boosting, Random Forest, and Decision Tree Classifier. Each model brings unique strengths to the predictive analytics framework, enhancing the robustness and reliability of the overall system.

1. Gradient Boosting:

- **Explanation:** Gradient Boosting is an ensemble learning method that builds a series of weak learners (typically decision trees) sequentially. Each subsequent model corrects the errors of the previous ones, leading to a strong predictive model.
- **Benefits:** It is highly effective in capturing complex relationships in the data and minimizing prediction errors.

2. Random Forest:

- **Explanation:** Random Forest is an ensemble learning method that constructs a multitude of decision trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees.
- **Benefits:** It excels in handling a large number of features and provides robust predictions by reducing overfitting.

3. Decision Tree Classifier:

- **Explanation:** A Decision Tree Classifier is a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility.
- **Benefits:** Decision trees are intuitive, easy to interpret, and can capture both linear and non-linear relationships in the data

Benefits of Model Training:

- *Model Diversity*: Incorporates diverse models for a comprehensive understanding of startup prediction.
- *Ensemble Learning*: Enhances predictive accuracy through the combination of multiple models.

6. Results Presentation through Web Page

A user-friendly web page is designed to present the results, allowing stakeholders to interactively explore and select the desired model for predictions. This interactive platform enhances accessibility and usability.

Benefits:

- *User Interaction*: Enables stakeholders to interactively explore and choose the desired predictive model.
- *Accessibility*: Enhances the accessibility of predictive analytics outcomes.

7. Displaying ROC Curve after Model Training

The ROC (Receiver Operating Characteristic) curve is a powerful tool for evaluating and comparing the performance of classification models. After training each model, the ROC curve is displayed to provide a visual representation of its discriminative capabilities.

Benefits:

- *Performance Evaluation*: Offers a visual assessment of the model's ability to distinguish between classes.
- *Comparative Analysis*: Facilitates the comparison of performance across different models.

8. Training Model and Visualizing Results on USA Map Projection

The project extends beyond traditional visualizations by integrating geographical insights. The results of the trained models are visualized on a map of the USA, where each state is shaded based on the number of successful and unsuccessful startups. This spatial representation provides a unique perspective on regional startup dynamics.

Benefits:

- Geographical Context: Incorporates geographical insights into startup success prediction.
- Regional Analysis: Enables a nuanced understanding of startup outcomes across different states.

Each of these features contributes a vital component to the overarching goal of predicting startup success, offering a holistic and innovative approach to leveraging data and AI in the dynamic realm of startups, particularly in the context of AI startups in healthcare.

4.4 FLOW CHART

The Flow Chart of the project is given below:

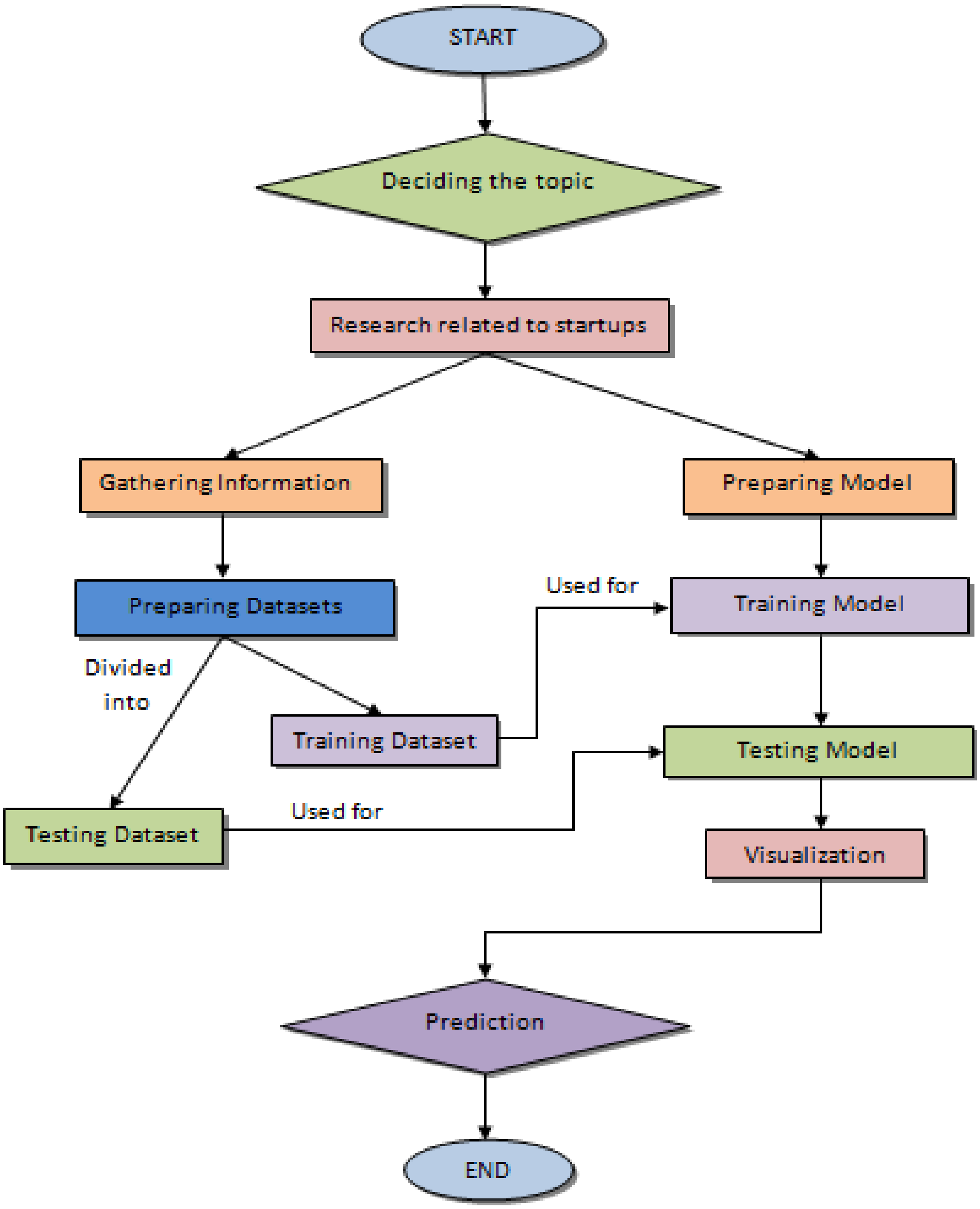


Figure 4.4.1 Basic Flow Chart of the project

4.5 SOFTWARE AND HARDWARE REQUIREMENTS

Software Requirements

1. Programming Language:

- **Python (Version 3.11.1):** Python serves as the core programming language for the project. It's widely used for data analysis, machine learning, and web development.

2. JavaScript:

Javascript was mainly used along with other web development tools for making our website user friendly. It helped in administering the responsiveness of our website and also as the main tool for creating visualizations and interactive charts and maps, which are the key features of our projects.

3. Database Management:

- **Excel (Microsoft Excel):** Microsoft Excel serves as the primary platform for the creation and storage of the project's database. It provides a familiar interface for data manipulation, analysis, and easy collaboration.

4. Libraries and Frameworks:

- **scikit-learn :** Scikit-learn is a machine learning library in Python. It provides simple tools for data mining and data analysis, making it a go-to choice for predictive modeling.
- **pandas :** Pandas is a data manipulation and analysis library. It's used for cleaning, transforming, and analyzing the dataset.
- **numpy :** NumPy is a fundamental package for scientific computing with Python. It provides support for large, multi-dimensional arrays and matrices, along with mathematical functions.
- **Flask :** Flask is a lightweight web framework in Python. It's used for developing the web application, especially for creating the API endpoints.
- **d3.js :** D3.js is a JavaScript library for producing dynamic, interactive data visualizations in web browsers. It's often used for creating interactive charts and maps.
- **Matplotlib :** Matplotlib is a 2D plotting library for Python. It's used for creating static, animated, and interactive visualizations in Python.

5. Web Development Tools :

- **HTML, CSS, JavaScript:** These are the standard technologies for building web pages and adding interactivity.
- **Flask (Web Framework):** Flask serves as the web framework for developing the backend of the web application. It was used mainly for the representation of the ROC Curve and the Map displayed on our website.

6. Integrated Development Environment (IDE):

- **Jupyter Notebook :** Jupyter Notebook is utilized specifically for visualization and factor selection tasks, providing an interactive computing environment suitable for data exploration and visualization.
- **Visual Studio Code (Version 1.84):** Visual Studio Code (VS Code) serves as the primary integrated development environment for coding, debugging, and version control. It provides a lightweight yet powerful environment for web development. Python visualization and many other tasks.

7. Cross-Browser Compatibility:

- **Ensure cross-browser compatibility (e.g., Chrome, Firefox, Safari, Edge):** The project works seamlessly across various web browsers.

Hardware Requirements

The hardware requirements for the project are relatively modest. A standard computer or laptop with sufficient processing power, memory, and storage capacity is suitable for development purposes.

1. Processor:

- **Multi-core processor (Recommended: Quad-core or higher):** A multi-core processor enhances the speed and efficiency of computations, crucial for machine learning tasks.

2. RAM:

- **Minimum of 8 GB RAM (Recommended: 12 GB or higher for large datasets):** Sufficient RAM is essential for handling large datasets and running machine learning models efficiently.

3. Storage:

- **Minimum of 50 GB free disk space for datasets and model storage:** Adequate storage space is required for storing datasets, models, and other project-related files.

4. Operating System:

- **Compatible with Windows, macOS, or Linux:** The project should be adaptable to various operating systems commonly used by developers.

5. Internet Connectivity:

- **Required for downloading libraries, datasets, and potential updates:** A stable internet connection is necessary for downloading dependencies, datasets, and any updates needed during the development process.

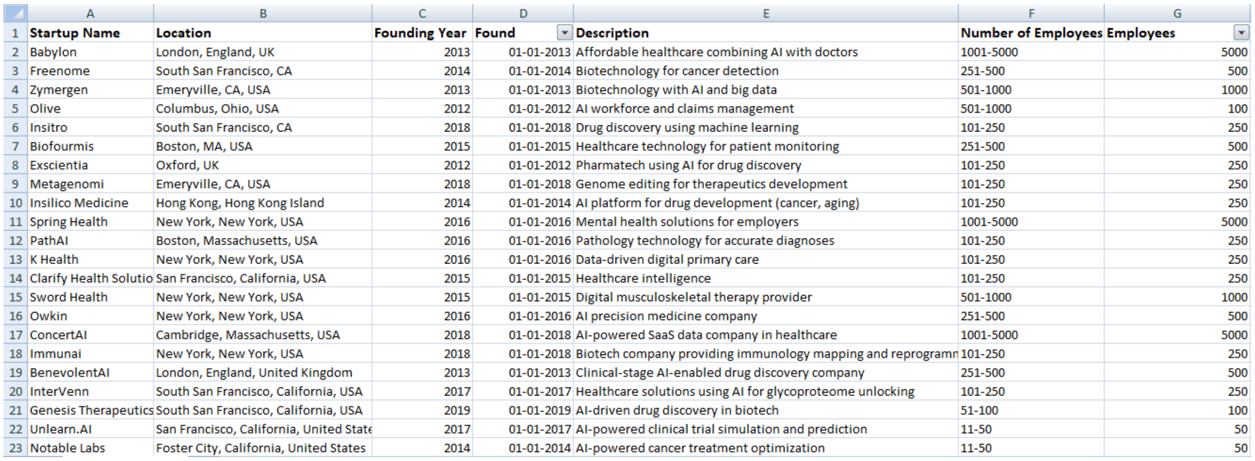
These requirements collectively form the foundation for the successful development and execution of your startup prediction project, empowering the decision-makers with a tool that transcends traditional predictive models, offering a nuanced understanding of success factors.

4.6 DATASET

In crafting our dataset, we meticulously curated information from reputable sources such as Crunchbase, Kaggle, and Wikipedia, amalgamating a rich and diverse collection of data to form the backbone of our predictive analytics framework.

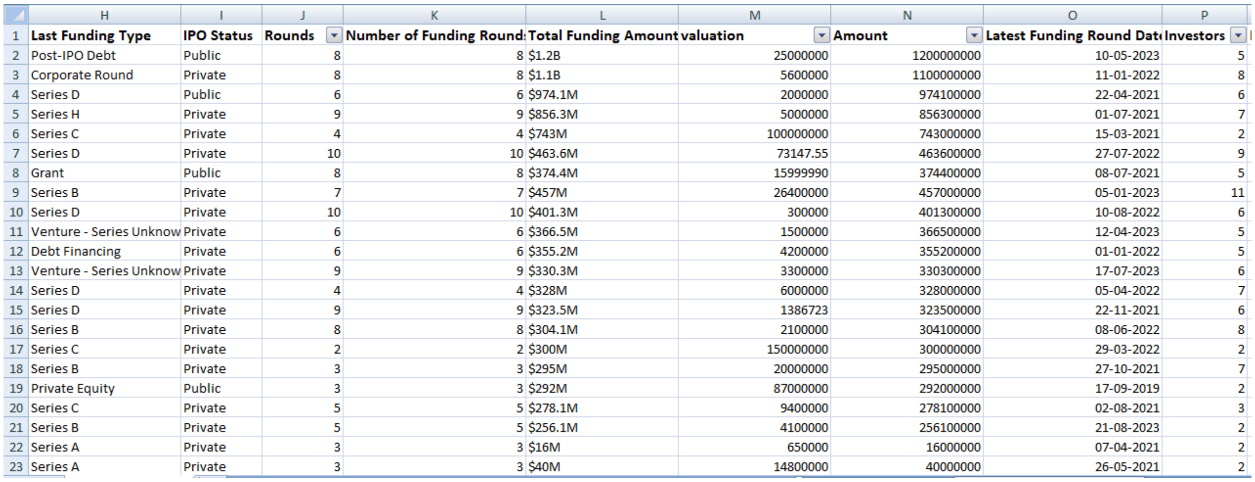
- Dataset.xlsx

The Dataset Excel sheet is the main data sheet including all the different details of different AI healthcare startups, such as their, Startup Name, Location, Founding Year, Description, Number of Employees, Funding Type, IPO Status, Number of Funding Rounds, Total Funding, Valuation, Last Funding Round Date, Number of Investors, Number of Lead Investors, Number of Acquisitions, Number of Active Technologies and their Success Label.



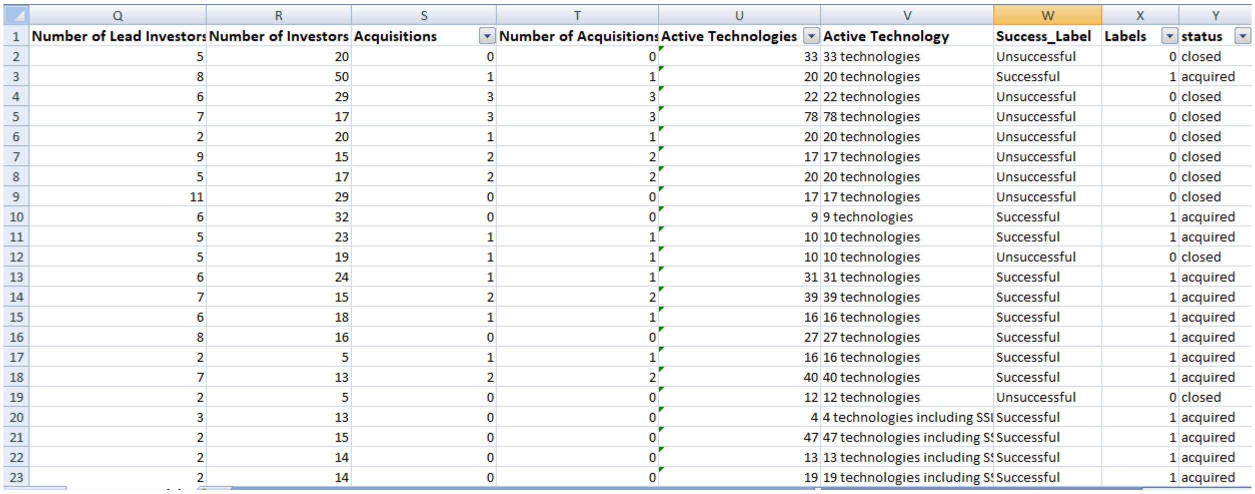
	A	B	C	D	E	F	G
1	Startup Name	Location	Founding Year	Found	Description	Number of Employees	Employees
2	Babylon	London, England, UK	2013	01-01-2013	Affordable healthcare combining AI with doctors	1001-5000	5000
3	Freenome	South San Francisco, CA	2014	01-01-2014	Biotechnology for cancer detection	251-500	500
4	Zymergen	Emeryville, CA, USA	2013	01-01-2013	Biotechnology with AI and big data	501-1000	1000
5	Olive	Columbus, Ohio, USA	2012	01-01-2012	AI workforce and claims management	501-1000	100
6	Insitro	South San Francisco, CA	2018	01-01-2018	Drug discovery using machine learning	101-250	250
7	Biofourmis	Boston, MA, USA	2015	01-01-2015	Healthcare technology for patient monitoring	251-500	500
8	Exscientia	Oxford, UK	2012	01-01-2012	Pharmatech using AI for drug discovery	101-250	250
9	Metagenomi	Emeryville, CA, USA	2018	01-01-2018	Genome editing for therapeutics development	101-250	250
10	Insilico Medicine	Hong Kong, Hong Kong Island	2014	01-01-2014	AI platform for drug development (cancer, aging)	101-250	250
11	Spring Health	New York, New York, USA	2016	01-01-2016	Mental health solutions for employers	1001-5000	5000
12	PathAI	Boston, Massachusetts, USA	2016	01-01-2016	Pathology technology for accurate diagnoses	101-250	250
13	K Health	New York, New York, USA	2016	01-01-2016	Data-driven digital primary care	101-250	250
14	Clarify Health Solutio	San Francisco, California, USA	2015	01-01-2015	Healthcare intelligence	101-250	250
15	Sword Health	New York, New York, USA	2015	01-01-2015	Digital musculoskeletal therapy provider	501-1000	1000
16	Owkin	New York, New York, USA	2016	01-01-2016	AI precision medicine company	251-500	500
17	ConcertAI	Cambridge, Massachusetts, USA	2018	01-01-2018	AI-powered SaaS data company in healthcare	1001-5000	5000
18	Immunai	New York, New York, USA	2018	01-01-2018	Biotech company providing immunology mapping and reprogramn	101-250	250
19	BenevolentAI	London, England, United Kingdom	2013	01-01-2013	Clinical-stage AI-enabled drug discovery company	251-500	500
20	InterVenn	South San Francisco, California, USA	2017	01-01-2017	Healthcare solutions using AI for glycoproteome unlocking	101-250	250
21	Genesis Therapeutics	South San Francisco, California, USA	2019	01-01-2019	AI-driven drug discovery in biotech	51-100	100
22	Unlearn.AI	San Francisco, California, United State	2017	01-01-2017	AI-powered clinical trial simulation and prediction	11-50	50
23	Notable Labs	Foster City, California, United States	2014	01-01-2014	AI-powered cancer treatment optimization	11-50	50

Figure 4.6.1 Dataset.xlsx (1)



	H	I	J	K	L	M	N	O	P
1	Last Funding Type	IPO Status	Rounds	Number of Funding Round	Total Funding Amount	valuation	Amount	Latest Funding Round Dat	Investors
2	Post-IPO Debt	Public	8	8	$1.2B	25000000	1200000000	10-05-2023	5
3	Corporate Round	Private	8	8	$1.1B	5600000	1100000000	11-01-2022	8
4	Series D	Public	6	6	$974.1M	2000000	974100000	22-04-2021	6
5	Series H	Private	9	9	$856.3M	5000000	856300000	01-07-2021	7
6	Series C	Private	4	4	$743M	100000000	743000000	15-03-2021	2
7	Series D	Private	10	10	$463.6M	73147.55	463600000	27-07-2022	9
8	Grant	Public	8	8	$374.4M	15999990	374400000	08-07-2021	5
9	Series B	Private	7	7	$457M	26400000	457000000	05-01-2023	11
10	Series D	Private	10	10	$401.3M	300000	401300000	10-08-2022	6
11	Venture - Series Unknow	Private	6	6	$366.5M	1500000	366500000	12-04-2023	5
12	Debt Financing	Private	6	6	$355.2M	4200000	355200000	01-01-2022	5
13	Venture - Series Unknow	Private	9	9	$330.3M	3300000	330300000	17-07-2023	6
14	Series D	Private	4	4	$328M	6000000	328000000	05-04-2022	7
15	Series D	Private	9	9	$323.5M	1386723	323500000	22-11-2021	6
16	Series B	Private	8	8	$304.1M	2100000	304100000	08-06-2022	8
17	Series C	Private	2	2	$300M	150000000	300000000	29-03-2022	2
18	Series B	Private	3	3	$295M	20000000	295000000	27-10-2021	7
19	Private Equity	Public	3	3	$292M	87000000	292000000	17-09-2019	2
20	Series C	Private	5	5	$278.1M	9400000	278100000	02-08-2021	3
21	Series B	Private	5	5	$256.1M	4100000	256100000	21-08-2023	2
22	Series A	Private	3	3	$16M	650000	16000000	07-04-2021	2
23	Series A	Private	3	3	$40M	14800000	40000000	26-05-2021	2

Figure 4.6.2 Dataset.xlsx (2)



Number of Lead Investors	Number of Investors	Acquisitions	Number of Acquisitions	Active Technologies	Active Technology	Success_Label	Labels	status
5	20	0	0	33	33 technologies	Unsuccessful	0	closed
8	50	1	1	20	20 technologies	Successful	1	acquired
6	29	3	3	22	22 technologies	Unsuccessful	0	closed
7	17	3	3	78	78 technologies	Unsuccessful	0	closed
2	20	1	1	20	20 technologies	Unsuccessful	0	closed
9	15	2	2	17	17 technologies	Unsuccessful	0	closed
5	17	2	2	20	20 technologies	Unsuccessful	0	closed
11	29	0	0	17	17 technologies	Unsuccessful	0	closed
6	32	0	0	9	9 technologies	Successful	1	acquired
5	23	1	1	10	10 technologies	Successful	1	acquired
5	19	1	1	10	10 technologies	Unsuccessful	0	closed
6	24	1	1	31	31 technologies	Successful	1	acquired
7	15	2	2	39	39 technologies	Successful	1	acquired
6	18	1	1	16	16 technologies	Successful	1	acquired
8	16	0	0	27	27 technologies	Successful	1	acquired
2	5	1	1	16	16 technologies	Successful	1	acquired
7	13	2	2	40	40 technologies	Successful	1	acquired
2	5	0	0	12	12 technologies	Unsuccessful	0	closed
3	13	0	0	4	4 technologies including SSI	Successful	1	acquired
2	15	0	0	47	47 technologies including S	Successful	1	acquired
2	14	0	0	13	13 technologies including S	Successful	1	acquired
2	14	0	0	19	19 technologies including S	Successful	1	acquired

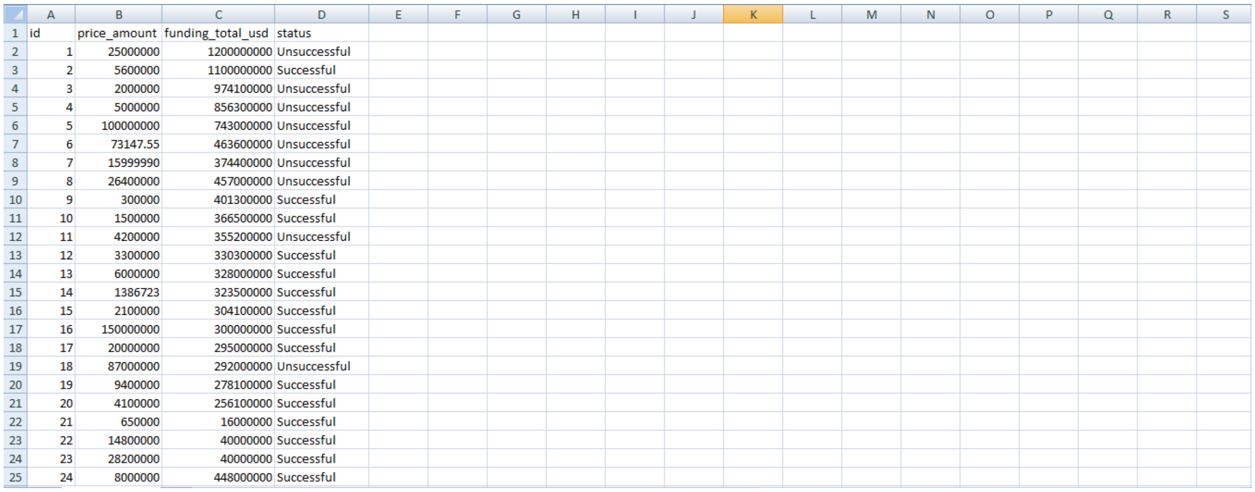
Figure 4.6.3 Dataset.xlsx (3)

The main data was broken into two halves one for training the models and the other for testing the models:

- **train-data.csv**

- **test-data.xlsx**

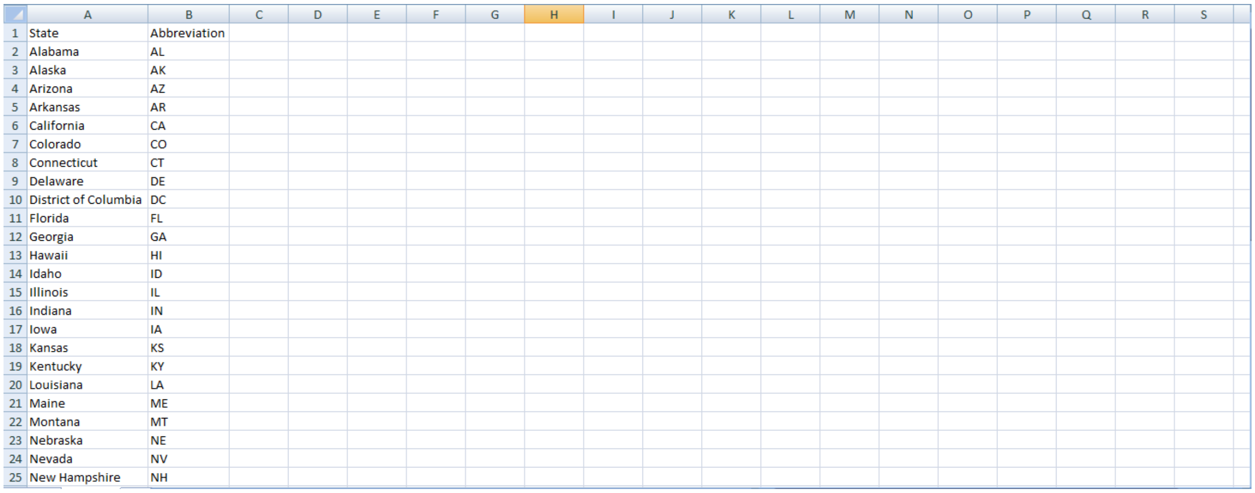
Another Data sheet comprises of the funding data, involving the valuation amount and the total funding amount for finding a relation between these two:



id	price_amount	funding_total_usd	status
1	25000000	1200000000	Unsuccessful
2	5600000	1100000000	Successful
3	2000000	974100000	Unsuccessful
4	5000000	856300000	Unsuccessful
5	100000000	743000000	Unsuccessful
6	73147.55	463600000	Unsuccessful
7	15999990	374400000	Unsuccessful
8	26400000	457000000	Unsuccessful
9	300000	401300000	Successful
10	1500000	366500000	Successful
11	4200000	355200000	Unsuccessful
12	3300000	330300000	Successful
13	6000000	328000000	Successful
14	1386723	323500000	Successful
15	2100000	304100000	Successful
16	150000000	300000000	Successful
17	20000000	295000000	Successful
18	87000000	292000000	Unsuccessful
19	9400000	278100000	Successful
20	4100000	256100000	Successful
21	650000	16000000	Successful
22	14800000	40000000	Successful
23	28200000	40000000	Successful
24	8000000	448000000	Successful

Figure 4.6.4 funding-data.csv

Another csv file contained all the US States along with their Abbreviations so that the model can be easily trained and we could predict success of the startups based on geographical area.



	A	B
1	State	Abbreviation
2	Alabama	AL
3	Alaska	AK
4	Arizona	AZ
5	Arkansas	AR
6	California	CA
7	Colorado	CO
8	Connecticut	CT
9	Delaware	DE
10	District of Columbia	DC
11	Florida	FL
12	Georgia	GA
13	Hawaii	HI
14	Idaho	ID
15	Illinois	IL
16	Indiana	IN
17	Iowa	IA
18	Kansas	KS
19	Kentucky	KY
20	Louisiana	LA
21	Maine	ME
22	Montana	MT
23	Nebraska	NE
24	Nevada	NV
25	New Hampshire	NH

Figure 4.6.5 states.csv

Lastly there was a JSON file that contained the coordinates of all the states of US and was essentially used by javascript to project the map of US during prediction visualization.

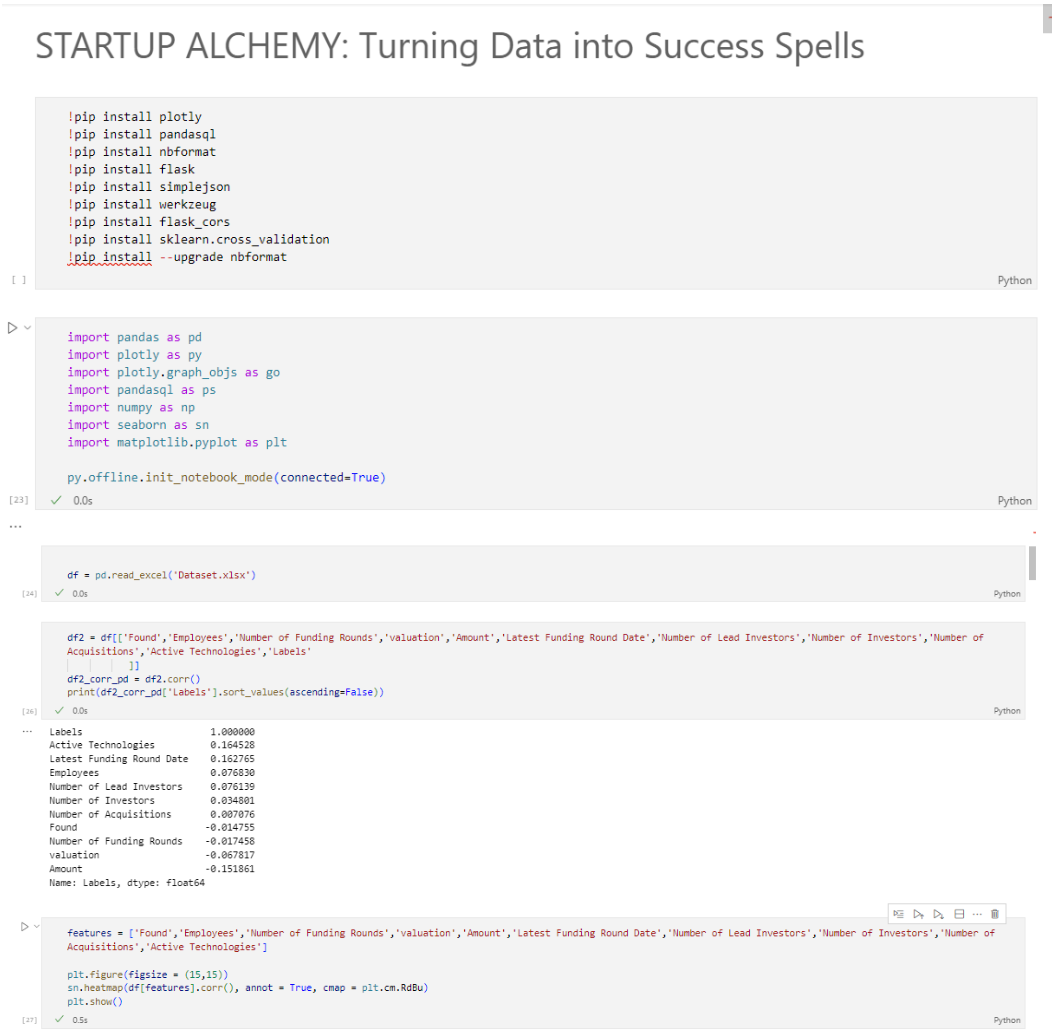
This meticulously self-curated dataset serves as the foundation for our project, reflecting a comprehensive amalgamation of information meticulously gathered from reputable sources. Its creation underscores our commitment to crafting a robust and reliable predictive analytics framework tailored to the intricacies of startup success.

4.7 CODE

Following are the key snippets of code that form the backbone of our startup success prediction system. Each code snippet is carefully annotated to elucidate its role and significance in the overall framework, offering insights into the intricacies of model training, data visualization, and predictive analytics.

1. Visualization for selecting factors.

The following is code from python Notebook that showcase various visualizations for selecting various key factors that affect the success of a startup.



STARTUP ALCHEMY: Turning Data into Success Spells

```
!pip install plotly
!pip install pandasql
!pip install nbformat
!pip install flask
!pip install simplejson
!pip install werkzeug
!pip install flask_cors
!pip install sklearn.cross_validation
!pip install --upgrade nbformat
```

```
import pandas as pd
import plotly as py
import plotly.graph_objs as go
import pandasql as ps
import numpy as np
import seaborn as sn
import matplotlib.pyplot as plt

py.offline.init_notebook_mode(connected=True)
```

[23] ✓ 0.0s

```
df = pd.read_excel('Dataset.xlsx')
```

[24] ✓ 0.0s

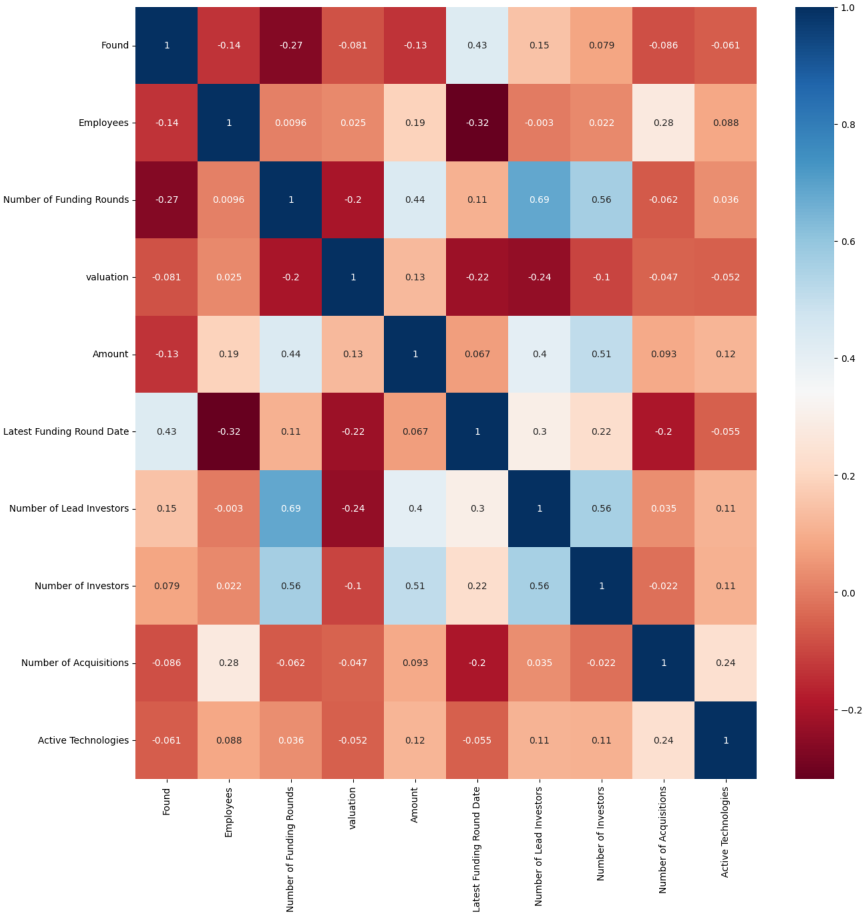
```
df2 = df[['Found','Employees','Number of Funding Rounds','valuation','Amount','Latest Funding Round Date','Number of Lead Investors','Number of Investors','Number of
Acquisitions','Active Technologies','Labels'
            ]]
df2_corr_pd = df2.corr()
print(df2_corr_pd['Labels'].sort_values(ascending=False))
```

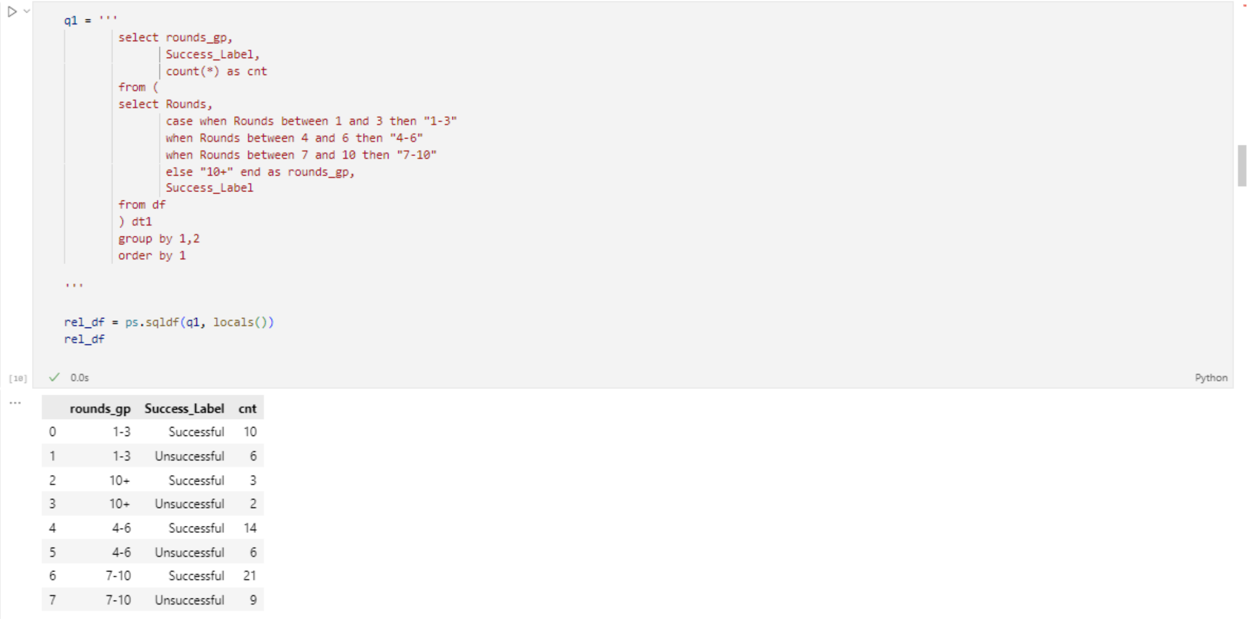
[26] ✓ 0.0s

```
Labels                      1.000000
Active Technologies         0.164528
Latest Funding Round Date   0.162765
Employees                   0.076830
Number of Lead Investors    0.076139
Number of Investors         0.034801
Number of Acquisitions      0.007076
Found                      -0.014755
Number of Funding Rounds   -0.017458
valuation                  -0.067817
Amount                     -0.151861
Name: Labels, dtype: float64
```

```
features = ['Found','Employees','Number of Funding Rounds','valuation','Amount','Latest Funding Round Date','Number of Lead Investors','Number of Investors','Number of
Acquisitions','Active Technologies']

plt.figure(figsize = (15,15))
sn.heatmap(df[features].corr(), annot = True, cmap = plt.cm.RdBu)
plt.show()
```

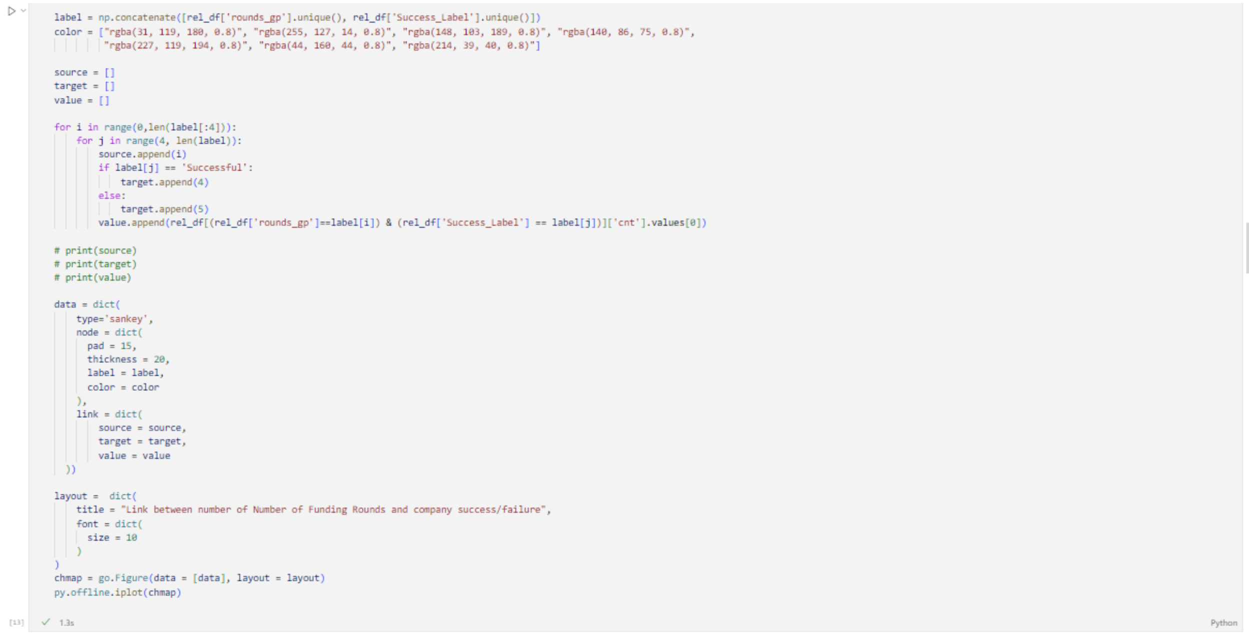
[27] ✓ 0.5s





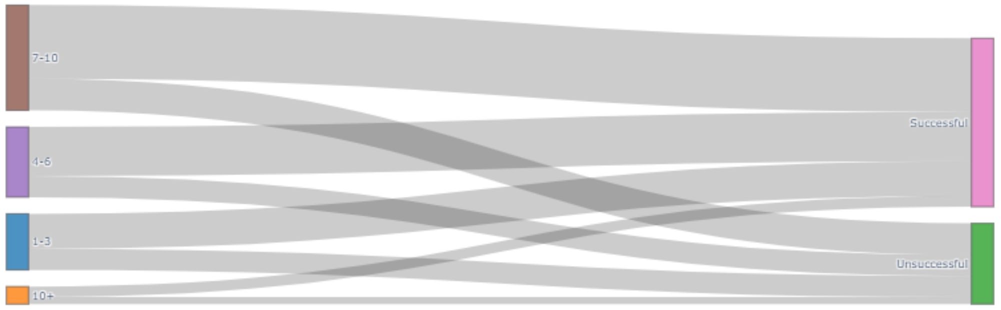
```
q1 = '''
        select rounds_gp,
               Success_Label,
               count(*) as cnt
        from (
        select Rounds,
               case when Rounds between 1 and 3 then "1-3"
               when Rounds between 4 and 6 then "4-6"
               when Rounds between 7 and 10 then "7-10"
               else "10+" end as rounds_gp,
               Success_Label
        from df
        ) dt1
        group by 1,2
        order by 1

'''

rel_df = ps.sqldf(q1, locals())
rel_df
```

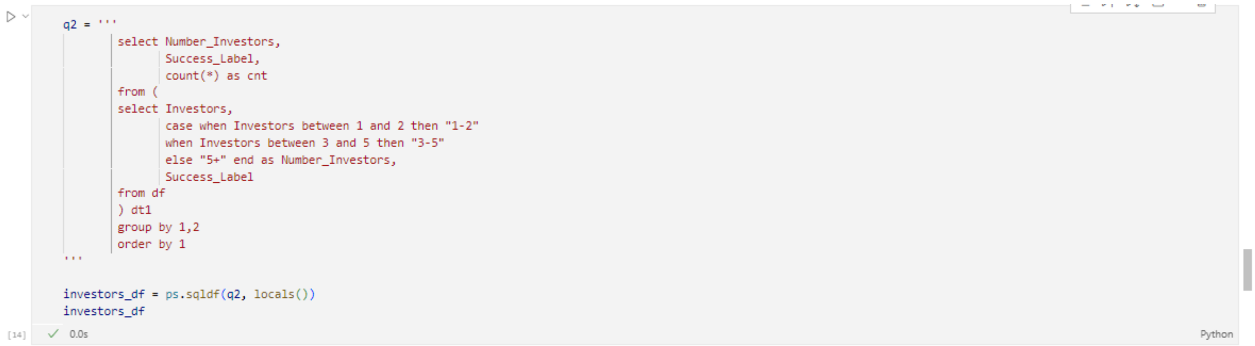
	rounds_gp	Success_Label	cnt
0	1-3	Successful	10
1	1-3	Unsuccessful	6
2	10+	Successful	3
3	10+	Unsuccessful	2
4	4-6	Successful	14
5	4-6	Unsuccessful	6
6	7-10	Successful	21
7	7-10	Unsuccessful	9



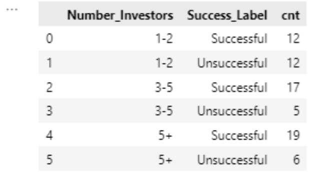
```
label = np.concatenate([rel_df['rounds_gp'].unique(), rel_df['Success_Label'].unique()])
color = ["rgba(31, 119, 180, 0.8)", "rgba(255, 127, 14, 0.8)", "rgba(148, 103, 189, 0.8)", "rgba(140, 86, 75, 0.8)",
         "rgba(227, 119, 194, 0.8)", "rgba(44, 160, 44, 0.8)", "rgba(214, 39, 40, 0.8)"]

source = []
target = []
value = []

for i in range(0,len(label[:4])):
    for j in range(4, len(label)):
        source.append(i)
        if label[j] == 'Successful':
            target.append(4)
        else:
            target.append(5)
        value.append(rel_df[(rel_df['rounds_gp']==label[i]) & (rel_df['Success_Label'] == label[j])]['cnt'].values[0])

# print(source)
# print(target)
# print(value)

data = dict(
    type='sankey',
    node = dict(
      pad = 15,
      thickness = 20,
      label = label,
      color = color
    ),
    link = dict(
        source = source,
        target = target,
        value = value
  ))

layout =  dict(
    title = "Link between number of Number of Funding Rounds and company success/failure",
    font = dict(
      size = 10
    )
)
chmap = go.Figure(data = [data], layout = layout)
py.offline.iplot(chmap)
```

Link between number of Number of Funding Rounds and company success/failure

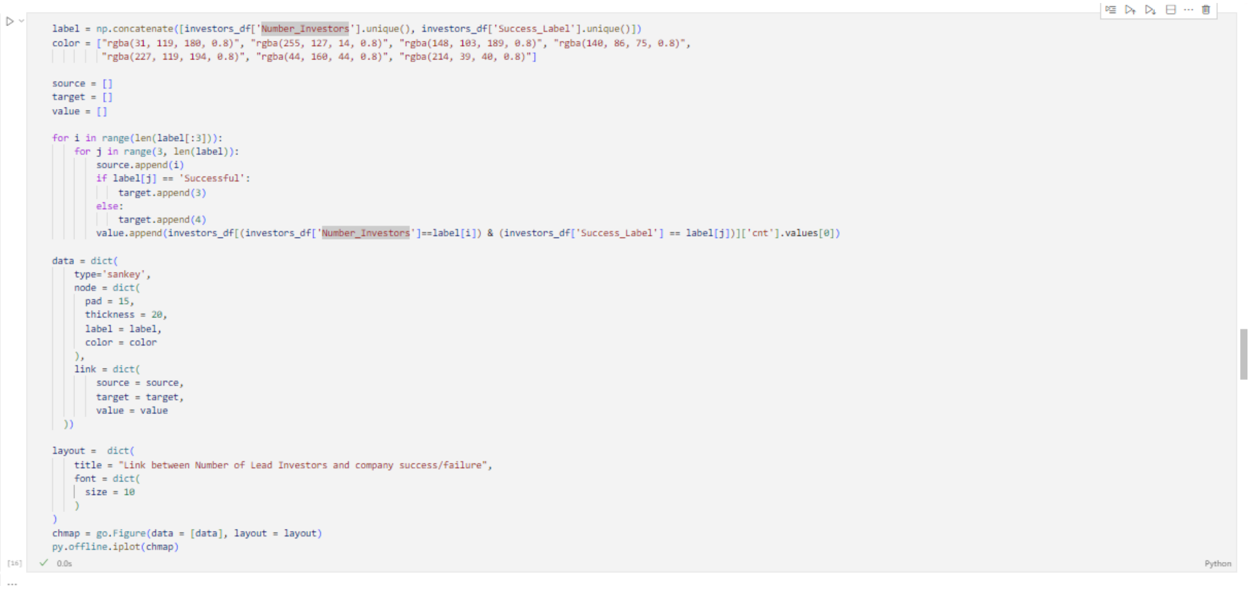




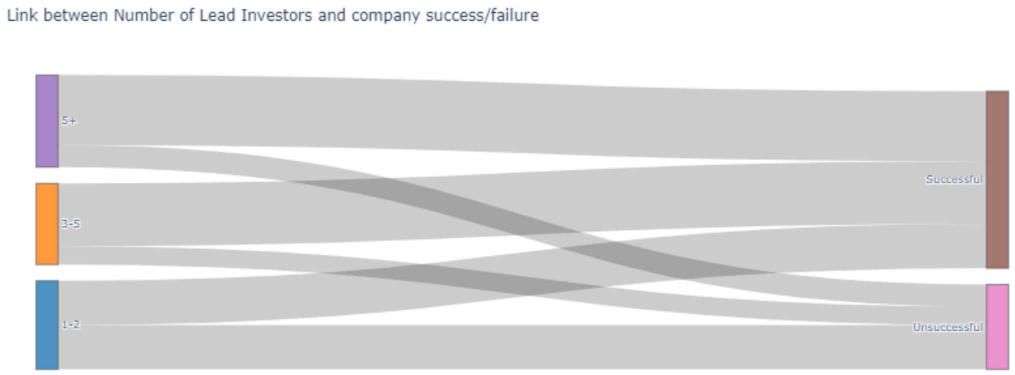
```
q2 = '''
        select Number_Investors,
               Success_Label,
               count(*) as cnt
        from (
        select Investors,
               case when Investors between 1 and 2 then "1-2"
               when Investors between 3 and 5 then "3-5"
               else "5+" end as Number_Investors,
               Success_Label
        from df
        ) dt1
        group by 1,2
        order by 1
'''

investors_df = ps.sqldf(q2, locals())
investors_df
```



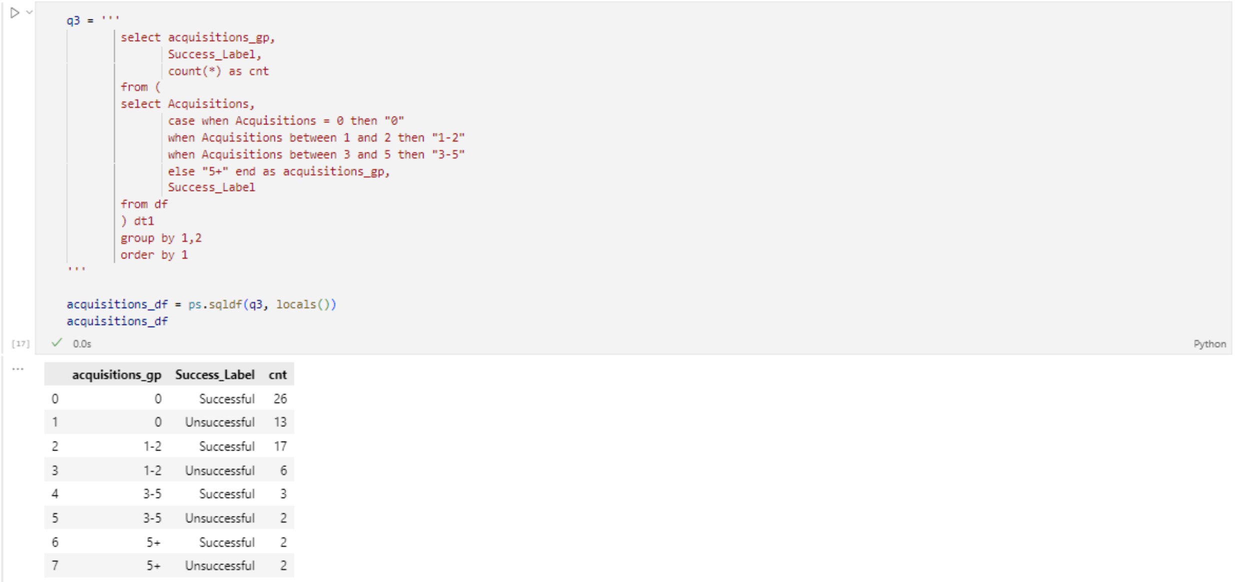
	Number_Investors	Success_Label	cnt
0	1-2	Successful	12
1	1-2	Unsuccessful	12
2	3-5	Successful	17
3	3-5	Unsuccessful	5
4	5+	Successful	19
5	5+	Unsuccessful	6



```python
label = np.concatenate([investors_df['Number_Investors'].unique(), investors_df['Success_Label'].unique()])
color = ["rgba(31, 119, 180, 0.8)", "rgba(255, 127, 14, 0.8)", "rgba(148, 103, 189, 0.8)", "rgba(140, 86, 75, 0.8)",
         "rgba(227, 119, 194, 0.8)", "rgba(44, 160, 44, 0.8)", "rgba(214, 39, 40, 0.8)"]

source = []
target = []
value = []

for i in range(len(label[:3])):
    for j in range(3, len(label)):
        source.append(i)
        if label[j] == 'Successful':
            target.append(3)
        else:
            target.append(4)
        value.append(investors_df[(investors_df['Number_Investors']==label[i]) & (investors_df['Success_Label'] == label[j])]['cnt'].values[0])

data = dict(
    type='sankey',
    node = dict(
      pad = 15,
      thickness = 20,
      label = label,
      color = color
    ),
    link = dict(
        source = source,
        target = target,
        value = value
  ))

layout =  dict(
    title = "Link between Number of Lead Investors and company success/failure",
    font = dict(
      size = 10
    )
)
chmap = go.Figure(data = [data], layout = layout)
py.offline.iplot(chmap)
```

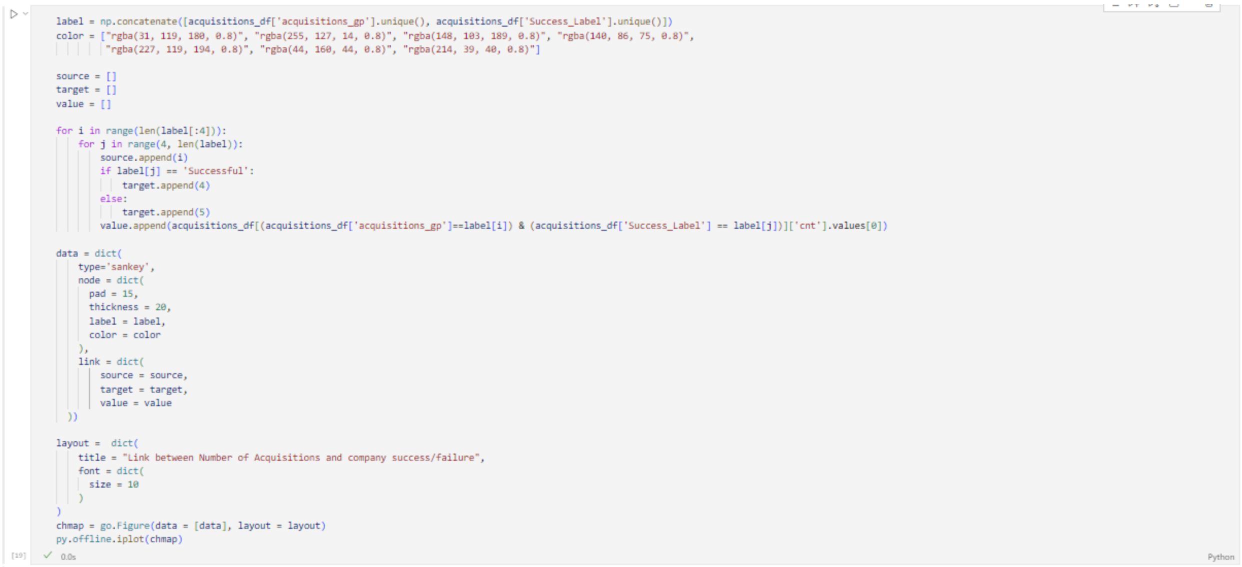


Link between Number of Lead Investors and company success/failure



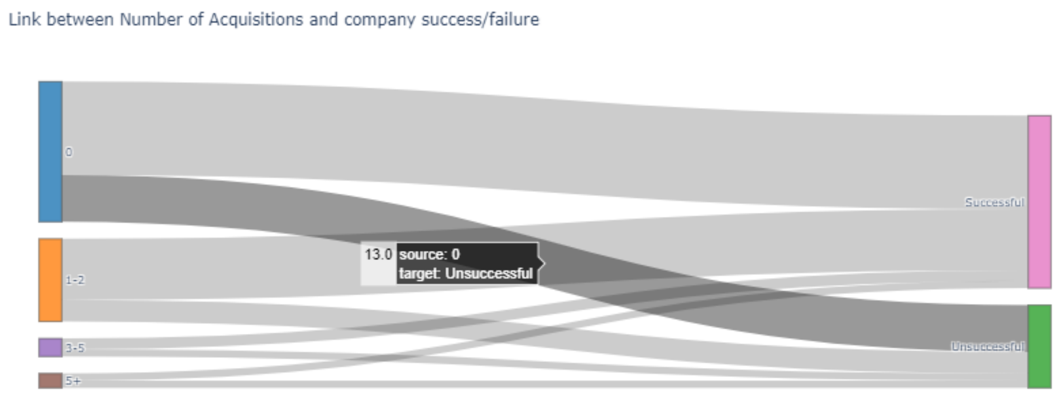
```python
q3 = '''
        select acquisitions_gp,
               Success_Label,
               count(*) as cnt
        from (
        select Acquisitions,
               case when Acquisitions = 0 then "0"
               when Acquisitions between 1 and 2 then "1-2"
               when Acquisitions between 3 and 5 then "3-5"
               else "5+" end as acquisitions_gp,
               Success_Label
        from df
        ) dt1
        group by 1,2
        order by 1
'''

acquisitions_df = ps.sqldf(q3, locals())
acquisitions_df
```

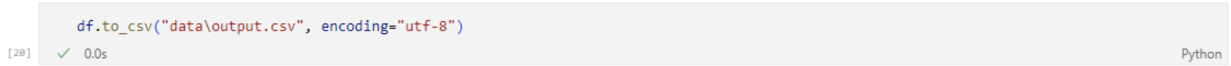
	acquisitions_gp	Success_Label	cnt
0	0	Successful	26
1	0	Unsuccessful	13
2	1-2	Successful	17
3	1-2	Unsuccessful	6
4	3-5	Successful	3
5	3-5	Unsuccessful	2
6	5+	Successful	2
7	5+	Unsuccessful	2



```python
label = np.concatenate([acquisitions_df['acquisitions_gp'].unique(), acquisitions_df['Success_Label'].unique()])
color = ["rgba(31, 119, 180, 0.8)", "rgba(255, 127, 14, 0.8)", "rgba(148, 103, 189, 0.8)", "rgba(140, 86, 75, 0.8)",
         "rgba(227, 119, 194, 0.8)", "rgba(44, 160, 44, 0.8)", "rgba(214, 39, 40, 0.8)"]

source = []
target = []
value = []

for i in range(len(label[:4])):
    for j in range(4, len(label)):
        source.append(i)
        if label[j] == 'Successful':
            target.append(4)
        else:
            target.append(5)
        value.append(acquisitions_df[(acquisitions_df['acquisitions_gp']==label[i]) & (acquisitions_df['Success_Label'] == label[j])]['cnt'].values[0])

data = dict(
    type='sankey',
    node = dict(
      pad = 15,
      thickness = 20,
      label = label,
      color = color
    ),
    link = dict(
        source = source,
        target = target,
        value = value
  ))

layout =  dict(
    title = "Link between Number of Acquisitions and company success/failure",
    font = dict(
      size = 10
    )
)
chmap = go.Figure(data = [data], layout = layout)
py.offline.iplot(chmap)
```

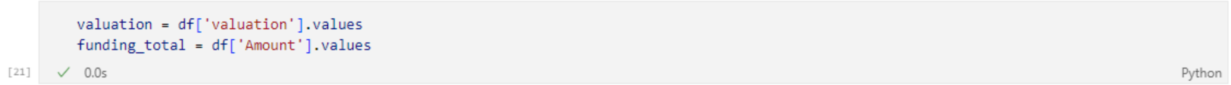
[19] ✓ 0.0s Python





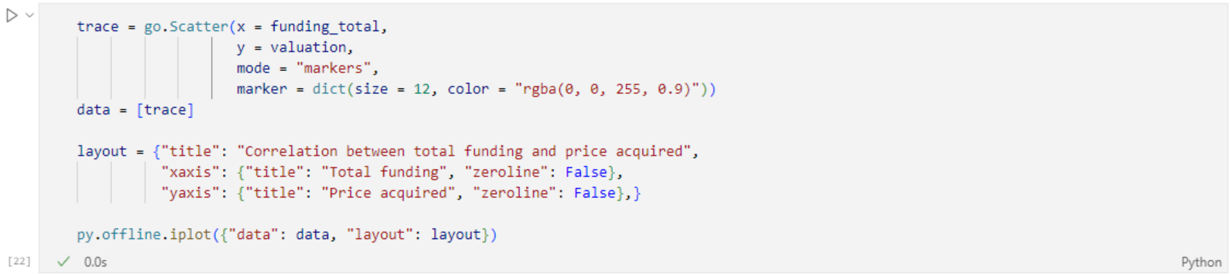
```python
df.to_csv("data\output.csv", encoding="utf-8")
```

[20] ✓ 0.0s Python



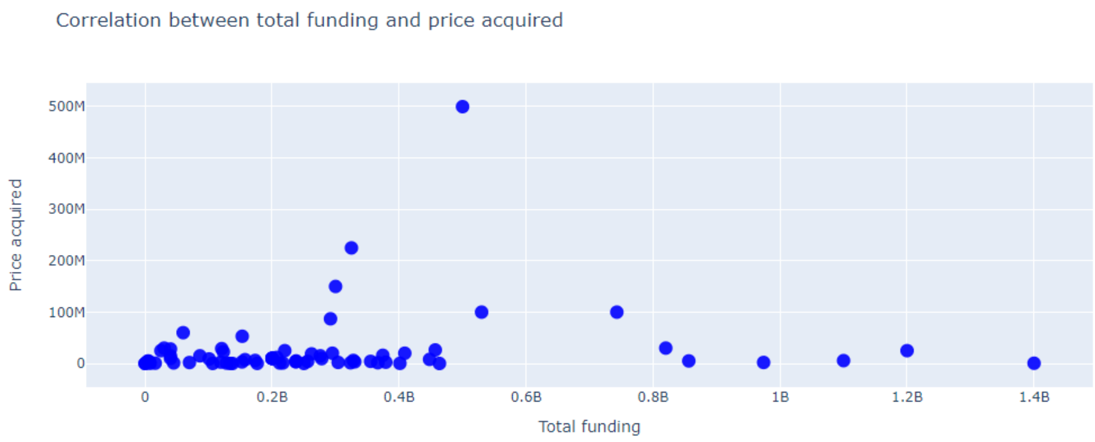
```python
valuation = df['valuation'].values
funding_total = df['Amount'].values
```

[21] ✓ 0.0s Python



```python
trace = go.Scatter(x = funding_total,
                   y = valuation,
                   mode = "markers",
                   marker = dict(size = 12, color = "rgba(0, 0, 255, 0.9)"))
data = [trace]

layout = {"title": "Correlation between total funding and price acquired",
          "xaxis": {"title": "Total funding", "zeroline": False},
          "yaxis": {"title": "Price acquired", "zeroline": False},}

py.offline.iplot({"data": data, "layout": layout})
```

[22] ✓ 0.0s Python



The code meticulously selects key features, including the number of funding rounds, the number of lead investors, and the number of acquisitions, exemplifying their impact on startup outcomes. The visualizations include insightful Sankey plots that unravel the intricate relationships between these variables. Additionally, a correlation scatter plot between the price acquired and the total funding amount provides a nuanced understanding of the financial dynamics.

2. Training of Models

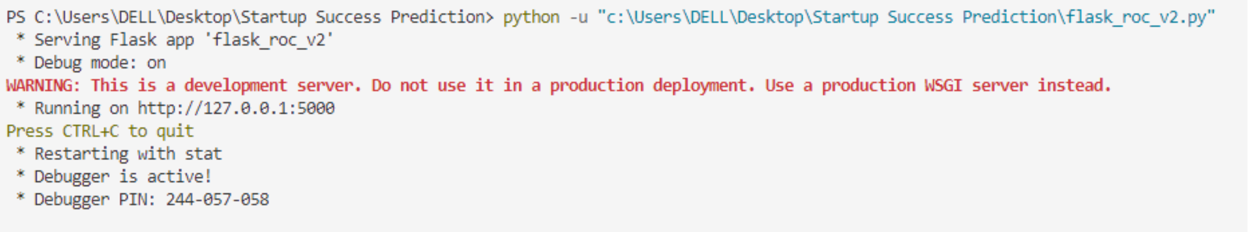
The following python code trains 3 different models- Gradient Boosting, Decision Tree and Random Forest, simultaneously, upon the data being loaded using Flask Cors that fulfils the server domain request from the designed web page.

```
import pandas as pd
import numpy as np
from sklearn.metrics import roc_curve
from sklearn import metrics
from flask_cors import CORS
import simplejson as json
from flask import Flask, stream_with_context
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from io import StringIO
from werkzeug.datastructures import Headers
from werkzeug.wrappers import Response
import csv
from sklearn.tree import DecisionTreeClassifier

app = Flask(__name__)
CORS(app)
```

```
@app.route('/roc_curve/m=<m>/d=<d>/l=<l>/n=<n>/c=<c>', methods=['GET'])
def roc_curve(m,d,l,n,c):
    if m == "model1":
        model = GradientBoostingClassifier(criterion = 'friedman_mse', learning_rate = 
float(c),
                                      loss = 'log_loss', max_depth = int(d),
                                      max_features = 'log2', max_leaf_nodes = int(l),
                                      n_estimators = int(n))
    elif m == "model2":
        model = RandomForestClassifier(criterion = 'entropy', max_depth = int(d),
                                       max_features = 'sqrt', max_leaf_nodes = int(l),
                                       n_estimators = int(n))
    else:
        model = DecisionTreeClassifier(max_depth = int(d),
                                       max_leaf_nodes = int(l))

    print("Roc",m,d,l,n,c)
    classifier = model.fit(X_train, y_train)
    print(model)
    y_pred = classifier.predict_proba(X_test)
    fpr, tpr, thresholds = metrics.roc_curve(y_test,y_pred[:,1],pos_label=1)
    result=[]
    for i in range(len(fpr)):
        result.append({"fpr":fpr[i],"tpr":tpr[i]})
    return json.dumps(result)

@app.route('/viz/m=<m>/d=<d>/l=<l>/n=<n>/c=<c>', methods=['GET'])
def viz(m,d,l,n,c):
    if m == "model1":
        model = GradientBoostingClassifier(criterion = 'friedman_mse', learning_rate = 
float(c),
                                      loss = 'log_loss', max_depth = int(d),
                                      max_features = 'log2', max_leaf_nodes = int(l),
                                      n_estimators = int(n))
    elif m == "model2":
        model = RandomForestClassifier(criterion = 'entropy', max_depth = int(d),
                                       max_features = None, max_leaf_nodes = int(l),
                                       n_estimators = int(n))
    else:
        model = DecisionTreeClassifier(max_depth = int(d),
                                       max_leaf_nodes = int(l))

    print("Viz",m,d,l,n,c)

    classifier = model.fit(X_train, y_train)
    print(model)
    X_new = test_df[features].values

    test_df['prob_acquired'] = classifier.predict_proba(X_new)[:,1]
    test_df['acquired'] = np.where(test_df['prob_acquired']>=0.5, 1, 0)
    test_df['closed'] = np.where(test_df['prob_acquired']<0.5, 1, 0)

    q1 = pd.merge(states_df, test_df, left_on = 'State', right_on = 'state', how =
'left')

    ren_col = {'prob_acquired': 'mean_prob_companies_acquired_by_state',
               'acquired': 'count_prob_companies_acquired_by_state',
               'closed': 'count_prob_companies_closed_by_state'}
    output_df = q1.groupby('State').agg({'prob_acquired': 'mean',
                             'acquired': 'sum',
                             'closed': 'sum'}).rename(columns = ren_col)
    output_df = output_df.reset_index()

    output_df.loc[output_df['mean_prob_companies_acquired_by_state'].isnull(),
'mean_prob_companies_acquired_by_state'] = 0
    output_df.loc[output_df['count_prob_companies_acquired_by_state'].isnull(),
'count_prob_companies_acquired_by_state'] = 0
    output_df.loc[output_df['count_prob_companies_closed_by_state'].isnull(),
'count_prob_companies_closed_by_state'] = 0

    def generate(output_df):
        d = StringIO()
        w = csv.writer(d)

        #write header
        w.writerow(tuple(output_df.columns))
        yield d.getvalue()
        d.seek(0)
        d.truncate(0)

        for i in range(output_df.shape[0]):
            w.writerow(tuple(output_df.iloc[i].values))
            yield d.getvalue()
            d.seek(0)
            d.truncate(0)

    # add a filename
    headers = Headers()
    headers.set('Content-Disposition', 'attachment', filename='log.csv')

    # stream the response as the data is generated
    return Response(
        stream_with_context(generate(output_df)),
        mimetype='text/csv', headers=headers
    )


train_df = pd.read_csv('data/train-data.csv', encoding = 'utf-8')
test_df = pd.read_excel('data/test-data.xlsx')
```

```
states_df = pd.read_csv('data/states.csv', encoding = 'utf-8')

features = ['Founding Year', 'Employees', 'Rounds',
             'valuation', 'Amount', 'Investors', 'Number of Investors',
             'Acquisitions', 'Active Technologies',
             ]
data = train_df[features + ['Labels']].values

X = data[:,:-1]
y = data[:,9]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.38775,
random_state = 0)

app.run(debug = True)
```

After training the models, an API endpoint is exposed, that allows other applications or services to interact with the trained model. This can be done using Flask to create routes that handle incoming requests, process the input data, and return the model's predictions.



```
PS C:\Users\DELL\Desktop\Startup Success Prediction> python -u "c:\Users\DELL\Desktop\Startup Success Prediction\flask_roc_v2.py"
 * Serving Flask app 'flask_roc_v2'
 * Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
 * Restarting with stat
 * Debugger is active!
 * Debugger PIN: 244-057-058
```

3. Web Application

- HTML (index.html)

```html
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>Startup Success Prediction: Model Development and Analysis</title>


  <link rel="stylesheet" href="styles.css">

  <!-- External scripts -->
  <script src="https://d3js.org/d3.v5.min.js"></script>
  <script src="https://cdnjs.cloudflare.com/ajax/libs/d3-legend/2.13.0/d3-legend.js"></script>
  <script type="text/javascript" src="./main.js"></script>


</head>

<body>
  <div id="tooltip" class="hidden">
    <p><span id="state"></span></p>
    <p><span id="acquired"></span></p>
    <p><span id="closed"></span></p>
    <p><span id="prob"></span></p>
  </div>

  <h1>STARTUP ALCHEMY: Turning Data into Success Spells</h1>

  <section>
    <!-- Model selection -->
    <label for="modelname">Choose a model:</label>
    <select id="modelname" onchange="chooseModel()">
      <option value="model1">Gradient Boosting</option>
      <option value="model3">Decision Trees</option>
      <option value="model2">Random Forests</option>
    </select>
    <br><br>

    <!-- Parameter input fields -->
    <table>
      <tr>
        <td>
          <div>
            <label for="depth">Max depth</label>
            <br><input type="number" id="depth"><br>
          </div>
        </td>

        <td>
          <div>
            <label for="leaf">Max leaf nodes</label>
            <br><input type="number" id="leaf"><br>
          </div>
        </td>

        <td>
          <div id = "estimators">
            <label for="estimators" >Number of estimators</label>
            <br><input type="number" id="estimator"><br>
          </div>
        </td>

        <td>
          <div id="lr">
            <label for="lr" >Learning rate</label>
            <br><input type="number" id="l"><br>
          </div>
        </td>
      </tr>
    </table>

    <br>

    <!-- Train and visualize buttons -->
    <input name="updateButton" type="button" id="train" value="Train model and draw ROC Curve" onclick="connectFlask()">
    &nbsp;&nbsp;&nbsp;&nbsp;
    <input name="visualize" type="button" id="viz" value="Train model, predict and visualize on new data" onclick="visualize()">
    <hr>

    <!-- Chart container -->
    <div id="chart1" class="chart-container"></div>
  </section>


</body>
</html>
```

- CSS (styles.css)

```css
body {
  font-family: 'Helvetica Neue', sans-serif;
  margin: 0;
  padding: 0;
  background-image: linear-gradient(to right, #3e4095, rgb(53, 174, 211));
  background-size: cover;
  color: #fff;
}

h1 {
  text-align: center;
  font-size: 3rem;
  font-weight: 700;
  color: #fff;
  margin-top: 2rem;
  padding: 1rem;
  background-color: rgba(0, 0, 0, 0.5);
  border-radius: 10px;
}

section {
  padding: 2rem;
  box-shadow: 0px 2px 10px rgba(0, 0, 0, 0.3);
  background-color: rgba(255, 255, 255, 0.9);
  border-radius: 10px;
  color:#1a1818;
}

/* Model selection */
#modelname {
  width: 200px;
  margin-right: 1rem;
  padding: 0.5rem;
  border: 1px solid #333;
  background-color: rgba(255, 255, 255, 0.9);
  border-radius: 5px;
}

/* Parameter input fields */
input[type="number"] {
  width: 120px;
  margin-bottom: 1rem;
  padding: 0.5rem;
  border: 1px solid #333;
  background-color: rgba(255, 255, 255, 0.9);
  border-radius: 5px;
}
```

```
/* Train and visualize buttons */
input[type="button"] {
  padding: 0.5rem 1rem;
  border: none;
  cursor: pointer;
  background-color: #333;
  color: #fff;
  border-radius: 5px;
}

input[type="button"]:hover {
  background-color: #555;
}

/* Charts */
.chart-container {
  width: 90%;
  margin: 0 auto;
  background-color: rgba(255, 255, 255, 0.9);
  overflow: hidden;
  padding: 20px;
  border-radius: 10px;
  color: #333;
}

/* Tooltip */
#tooltip {
  position: absolute;
  display: none;
  background-color: #333;
  color: #fff;
  padding: 10px;
  font-size: 14px;
  pointer-events: none;
  border-radius: 5px;
}


    th, td {
      padding: 10px;
      text-align: center;
      color:#333;
    }

    th {
      background-color: #555;
      color: #1a1818;
    }
```

- JAVASCRIPT (main.js)

```
function chooseModel(){
    var x = document.getElementById("modelname").value;

    if (x === "model2"){
        document.getElementById("lr").style.visibility="hidden";
        document.getElementById("estimators").style.visibility="visible";
    }
    if (x === "model3") {
        document.getElementById("lr").style.visibility="hidden";
        document.getElementById("estimators").style.visibility="hidden";
    }
    if (x === "model1") {
        document.getElementById("lr").style.visibility="visible";
        document.getElementById("estimators").style.visibility="visible";
    }
}

 function connectFlask() {
  var url = "http://127.0.0.1:5000/roc_curve/"
  var modelname = document.getElementById("modelname").value;
  var max_depth = document.getElementById("depth").value;
  var max_leaf_nodes = document.getElementById("leaf").value;
  var n_estimators = document.getElementById("estimator").value;
  var learning_rate = document.getElementById("l").value;

  if (learning_rate==="") {
    learning_rate = .1;
  }

  if (n_estimators==="") {
    n_estimators = 100;
  }

  if (max_depth==="") {
    max_depth = 5;
  }

  if (max_leaf_nodes==="") {
    max_leaf_nodes = 10;
  }

  url1 = url.concat("m=").concat(modelname).concat("/d=").concat(max_depth).concat("/l=").concat(max_leaf_nodes).concat("/n=").concat(n_estimators).concat("/c=").concat(learning_rate);


  d3.json(url1).then(function(data) {
    drawRoc(data);
  });
}




function drawRoc(data){

var w = 800;
var h = 450;
var padding = 50;

var xScale = d3.scaleLinear()
    .domain([0,1])
    .range([0, w/2])

var yScale = d3.scaleLinear()
    .domain([0,1])
    .range([h-h/10, 0]);

d3.select("#chart1")
    .selectAll("*")
    .remove();

var svg = d3.select("#chart1")
    .append("svg")
    .attr("width", w + padding)
    .attr("height", h + padding)
    .attr("align","center-right")
    .append("g")
    .attr("transform", "translate(" + 275 + "," + padding + ")");

svg.append("g")
    .attr("class", "x axis")
    .attr("transform", "translate(0," + (h-h/10) + ")")
    .call(d3.axisBottom(xScale));

svg.append("g")
    .attr("class", "y axis")
    .call(d3.axisLeft(yScale));

var rocline = d3.line()
   .x(function(d) { return xScale(d.fpr)})
   .y(function(d) { return yScale(d.tpr)});

svg.append("path")
    .datum(data)
    .attr("class", "line")
    .attr("d", rocline);
```

```
svg.append("line")
    .attr("x1", xScale(0))
    .attr("y1", yScale(0))
    .attr("x2", xScale(1))
    .attr("y2", yScale(1))
    .attr("stroke-width", 2)
    .attr("stroke", "black")
    .attr("stroke-dasharray", "8,8");


svg.append("text")
    .attr("transform", "rotate(0)")
    .attr("y", (padding + 380))
    .attr("x",180)
    .attr("dy", "1em")
    .text("False Positive Rate ");

svg.append("text")
    .attr("transform", "rotate(-90)")
    .attr("y", 0 - (padding/.9))
    .attr("x",0 - (h / 2))
    .attr("dy", "1em")
    .text("True Positive Rate ");
}


function visualize(){

    //Width and height
    var w = 1200;
    var h = 600;

    //Define map projection
    var projection = d3.geoAlbersUsa()
                           .translate([w/2-w/12, h/2])
                           .scale([1200]);
    //Define path generator
    var path = d3.geoPath()
                     .projection(projection);

    //Define quantize scale to sort data values into buckets of color
    var color = d3.scaleQuantize()
                        .range(['rgb(170, 237,
240)','rgb(253,174,97)','rgb(255,255,191)','rgb(166,217,106)','rgb(26,150,65)']);


    //Remove previous svg elements
    d3.select("#chart1")
    .selectAll("*")
    .remove();
```

```
  //Create SVG element
  var svg = d3.select("#chart1")
        .append("svg")
        .attr("width", w)
        .attr("height", h);

  var url = "http://127.0.0.1:5000/viz/"
  var modelname = document.getElementById("modelname").value;
  var learning_rate = document.getElementById("l").value;
  var max_depth = document.getElementById("depth").value;
  var max_leaf_nodes = document.getElementById("leaf").value;
  var n_estimators = document.getElementById("estimator").value;

  if (learning_rate==="") {
  learning_rate = .1;
 }

 if (n_estimators==="") {
  n_estimators = 100;
 }

 if (max_depth==="") {
  max_depth = 5;
 }

 if (max_leaf_nodes==="") {
  max_leaf_nodes = 10;
 }

 url1 =
url.concat("m=").concat(modelname).concat("/d=").concat(max_depth).concat("/l=").concat(m
ax_leaf_nodes).concat("/n=").concat(n_estimators).concat("/c=").concat(learning_rate);


      d3.csv(url1).then(function(data) {
        //Set input domain for color scale
        color.domain([
          d3.min(data, function(d) { return
d.mean_prob_companies_acquired_by_state; }),
          d3.max(data, function(d) { return
d.mean_prob_companies_acquired_by_state; })
        ]);
        //Load in GeoJSON data
        d3.json("\\data\\us-states.json").then(function(json) {
          //Merge the ag. data and GeoJSON
          //Loop through once for each ag. data value
          for (var i = 0; i < data.length; i++) {

            //Grab state name
            var dataState = data[i].State;
```

```
                        //Grab data value, and convert from string to float
                        var dataValue =
parseFloat(data[i].mean_prob_companies_acquired_by_state);

                        //Grab data value, and convert from string to float
                        var dataAcquired =
parseFloat(data[i].count_prob_companies_acquired_by_state);

                        //Grab data value, and convert from string to float
                        var dataClosed =
parseFloat(data[i].count_prob_companies_closed_by_state);


                        //Find the corresponding state inside the GeoJSON
                        for (var j = 0; j < json.features.length; j++) {

                            var jsonState = json.features[j].properties.name;

                            if (dataState == jsonState) {

                                //Copy the data value into the JSON
                                json.features[j].properties.value = dataValue;
                                json.features[j].properties.acquired = dataAcquired;
                                json.features[j].properties.closed = dataClosed;

                                //Stop looking through the JSON
                                break;

                            }
                        }
                    }
                    //Bind data and create one path per GeoJSON feature
                    svg.selectAll("path")
                       .data(json.features)
                       .enter()
                       .append("path")
                       .attr("d", path)
                       .style("fill", function(d) {
                            //Get data value
                            var value = d.properties.value;

                            if (value>=0) {
                                //If value exists…
                                return color(value);
                            } else {
                                //If value is undefined…
                                return "#ccc";
                            }
                       })
                       .style("fill-opacity", 1)
                       .style("stroke", "#a9a9a9")
                       .style("stroke-width", 1.5)
                       .on("mouseover", function(d) {
                    //Get this bar's x/y values, then augment for the tooltip
                    //Update the tooltip position and value
                    var coordinates = d3.mouse(this);
                    var xPosition = coordinates[0] + w/11;
                    var yPosition = coordinates[1] + h/2.25;
                    var format = d3.format(".4f");

                    d3.select("#tooltip")
                        .style("left", xPosition + "px")
                        .style("top", yPosition + "px")
                        .select("#state")
                        .text(d.properties.name);
                    d3.select("#tooltip")
                        .style("left", xPosition + "px")
                        .style("top", yPosition + "px")
                        .select("#acquired")
                        .text("Startups predicted to be successful: " +
d.properties.acquired);
                    d3.select("#tooltip")
                        .style("left", xPosition + "px")
                        .style("top", yPosition + "px")
                        .select("#closed")
                        .text("Startups predicted to fail: " + d.properties.closed);
                    d3.select("#tooltip")
                        .style("left", xPosition + "px")
                        .style("top", yPosition + "px")
                        .select("#prob")
                        .text("Mean probability of startups to be successful: " +
format(d.properties.value));

                    //Show the tooltip

                    d3.select("#tooltip").classed("hidden", false);
          d3.select("#tooltip").style("display", "block");
               })
               .on("mouseout", function() {

                    //Hide the tooltip
                    d3.select("#tooltip").classed("hidden", true);
                    d3.select("#tooltip").style("display", "none");
               });

                });
            var linear = d3.scaleQuantize()
              .domain([
                    d3.min(data, function(d) { return
d.mean_prob_companies_acquired_by_state; }),
                    d3.max(data, function(d) { return
d.mean_prob_companies_acquired_by_state; })
                ])
              .range(['rgb(170, 237,
240)','rgb(253,174,97)','rgb(255,255,191)','rgb(166,217,106)','rgb(26,150,65)']);

            var svg = d3.select("svg");

            svg.append("g")
              .attr("class", "legendLinear")
              .attr("transform", "translate(1000,200)");

            var legendLinear = d3.legendColor()
              .shape('rect')
              .shapeWidth(50)
              .shapePadding(5)
              .orient('vertical')
              .ascending(true)
              .scale(linear)
              ;

            svg.select(".legendLinear")
              .call(legendLinear);
            });
}
```

The integration of diverse data visualization techniques, machine learning model training, and the development of an interactive web application, through the above code, culminates in a comprehensive and powerful solution, laying the foundation for informed decision-making in the dynamic landscape of startup success prediction.

4.8 RESULTS

Results of Visualizations:

Our visualization efforts yielded insightful outcomes, illuminating key factors that influence startup success. Notably, sankey plots were employed to showcase relationships between the number of funding rounds, lead investors, and acquisitions. Additionally, a correlation scatter plot illustrated the nuanced connection between the price acquired and total funding amount. These visualizations, embedded within our exploratory data analysis, provide an intuitive understanding of the intricate interplay of variables in the startup ecosystem.

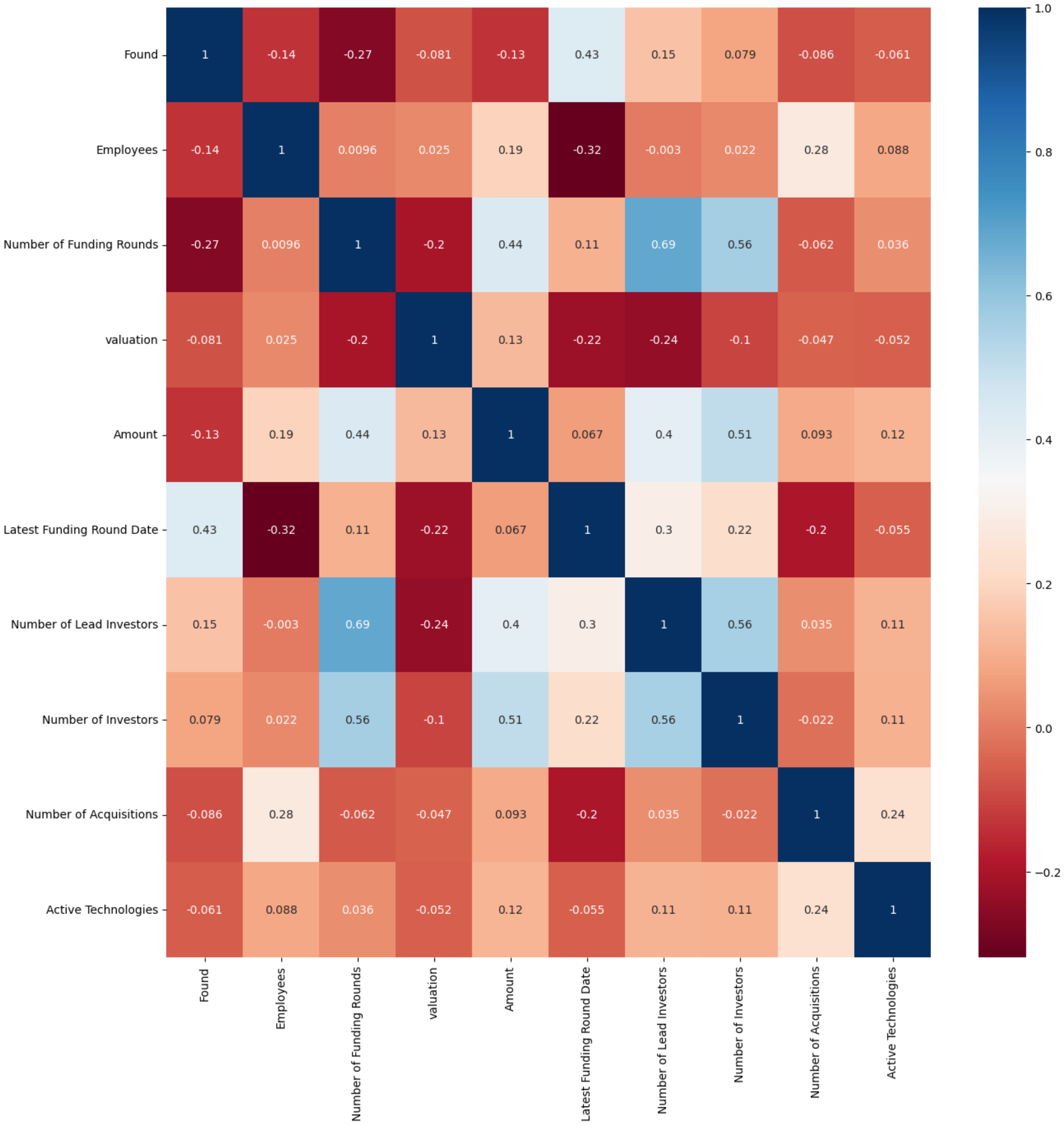


Figure 4.8.1 Correlation between success and other factors affecting the startup.

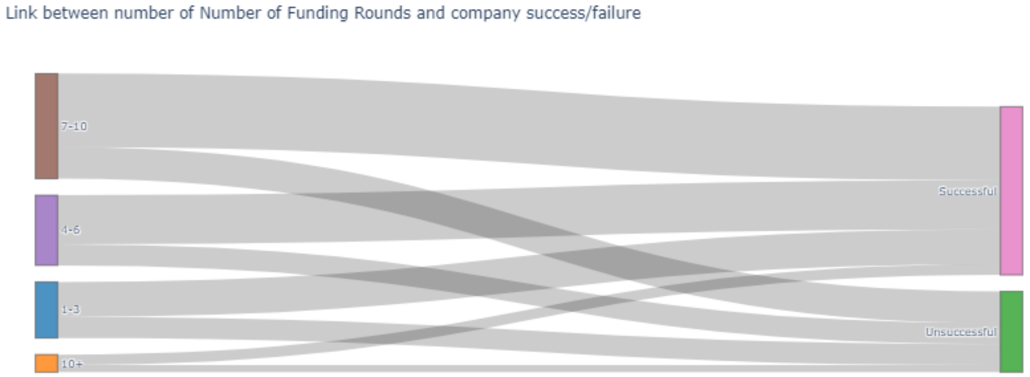


Figure 4.8.2 Sankey Plot 1

(between Funding Round and Success/Failure)

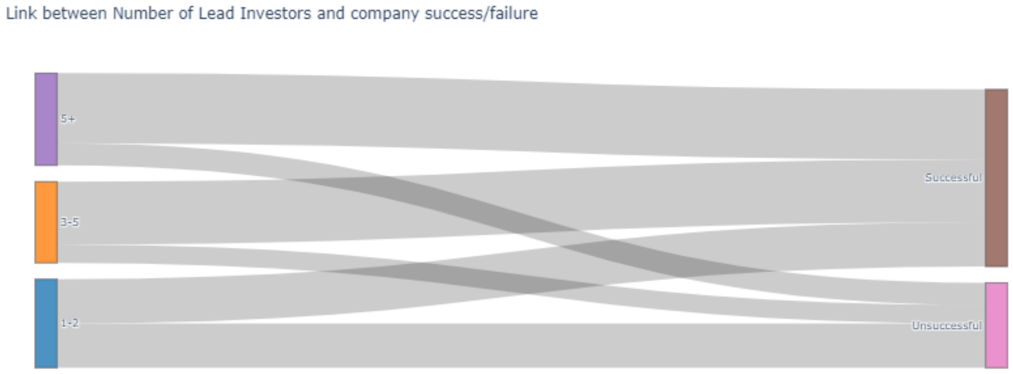


Figure 4.8.3 Sankey Plot 2

(between Number of Lead Investors and Success/Failure)

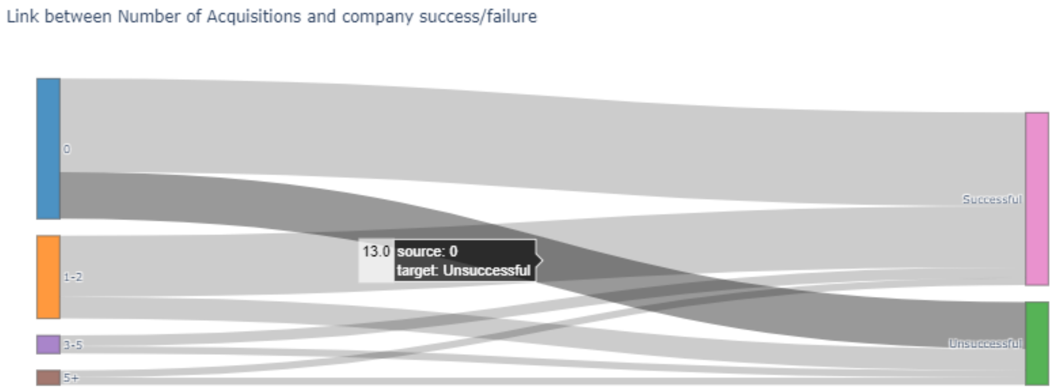


Figure 4.8.4 Sankey Plot 3

(between Number of Acquisitions and Success/Failure)

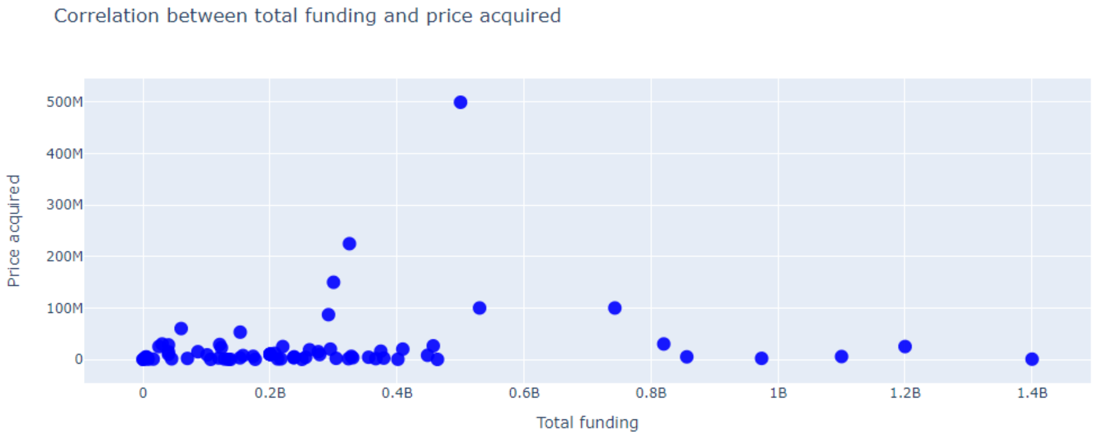
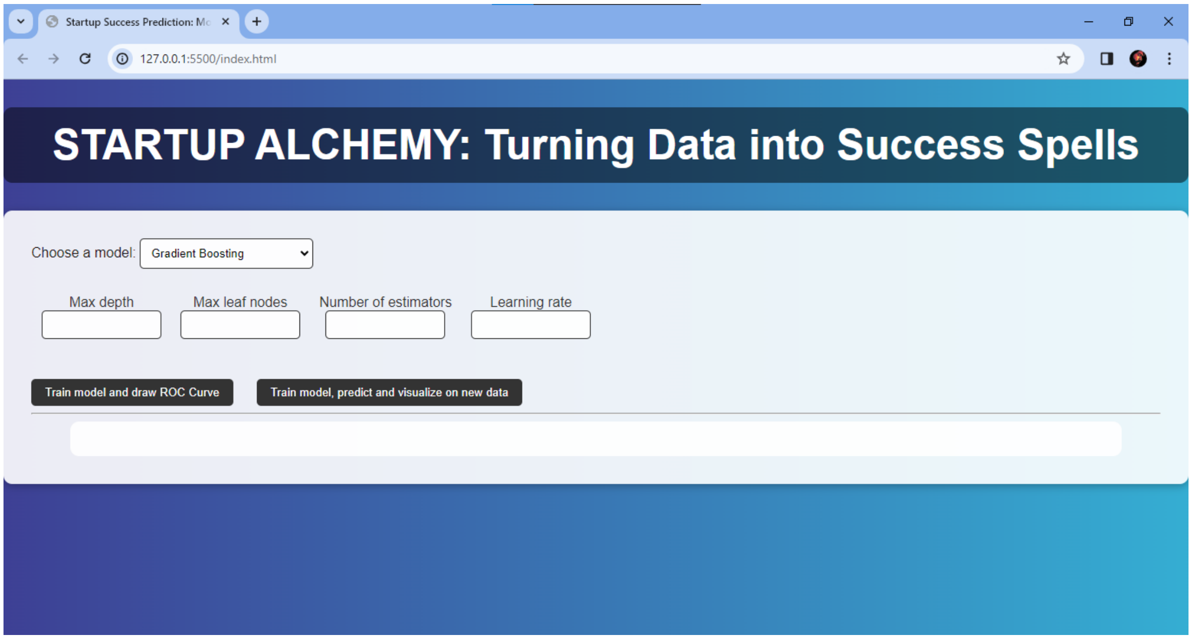


Figure 4.8.5 Scatter Plot

(showing Correlation between Price Acquired and Total Funding received)

Web Page:

The web page designed for showcasing prediction is user interactive and provides an option between 3 prediction models- Gradient Boosting, Decision Trees, Random Forests, and 2 kind of visualization for each model- ROC Curve and state wise Prediction on the map of US.



STARTUP ALCHEMY: Turning Data into Success Spells

Choose a model: Gradient Boosting

Max depth

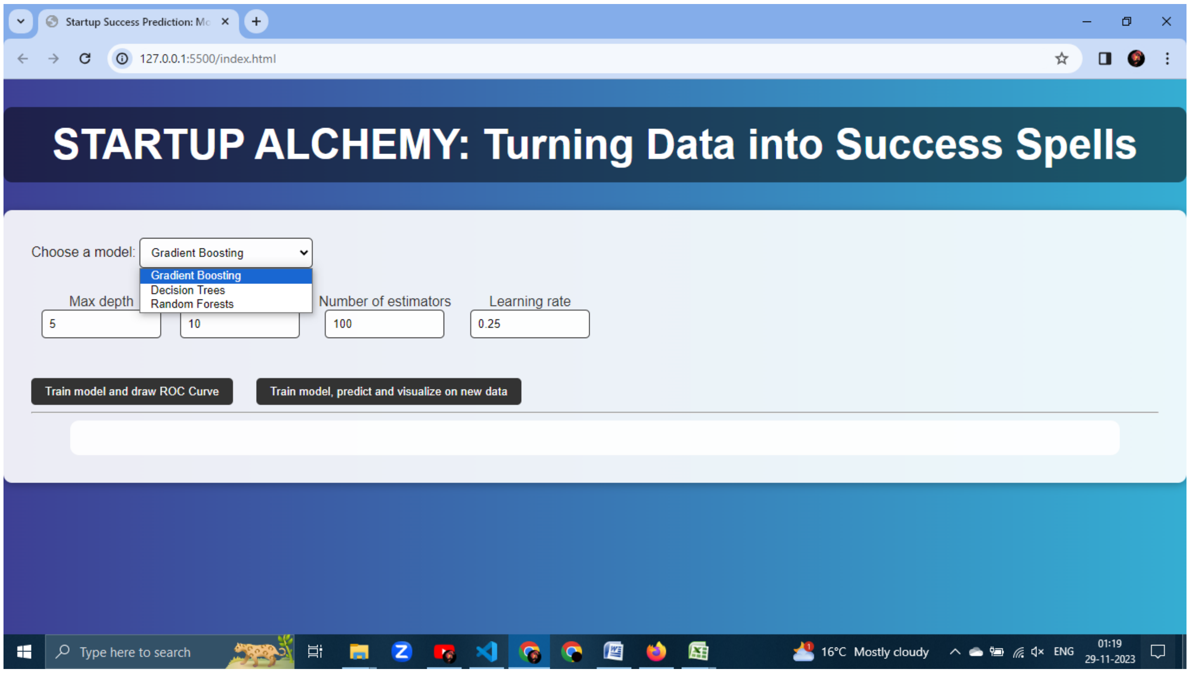
Max leaf nodes

Number of estimators

Learning rate

Startup Success Prediction: Mo
127.0.0.1:5500/index.html
Train model and draw ROC Curve
Train model, predict and visualize on new data

Figure 4.8.6 Web Page



STARTUP ALCHEMY: Turning Data into Success Spells

Choose a model: Gradient Boosting

Max depth: 5

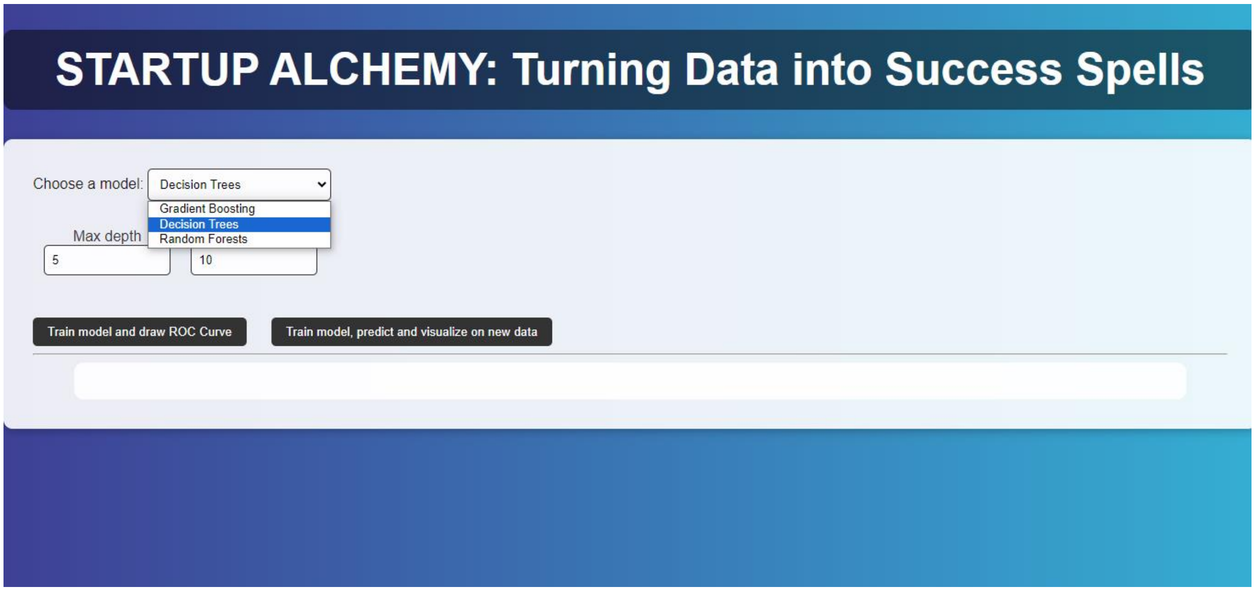
Max leaf nodes: 10

Number of estimators: 100

Learning rate: 0.25

Startup Success Prediction: Mo
127.0.0.1:5500/index.html
Gradient Boosting
Decision Trees
Random Forests
Train model and draw ROC Curve
Train model, predict and visualize on new data
Type here to search
16°C Mostly cloudy
ENG
01:19
29-11-2023

Figure 4.8.7 Model 1



STARTUP ALCHEMY: Turning Data into Success Spells

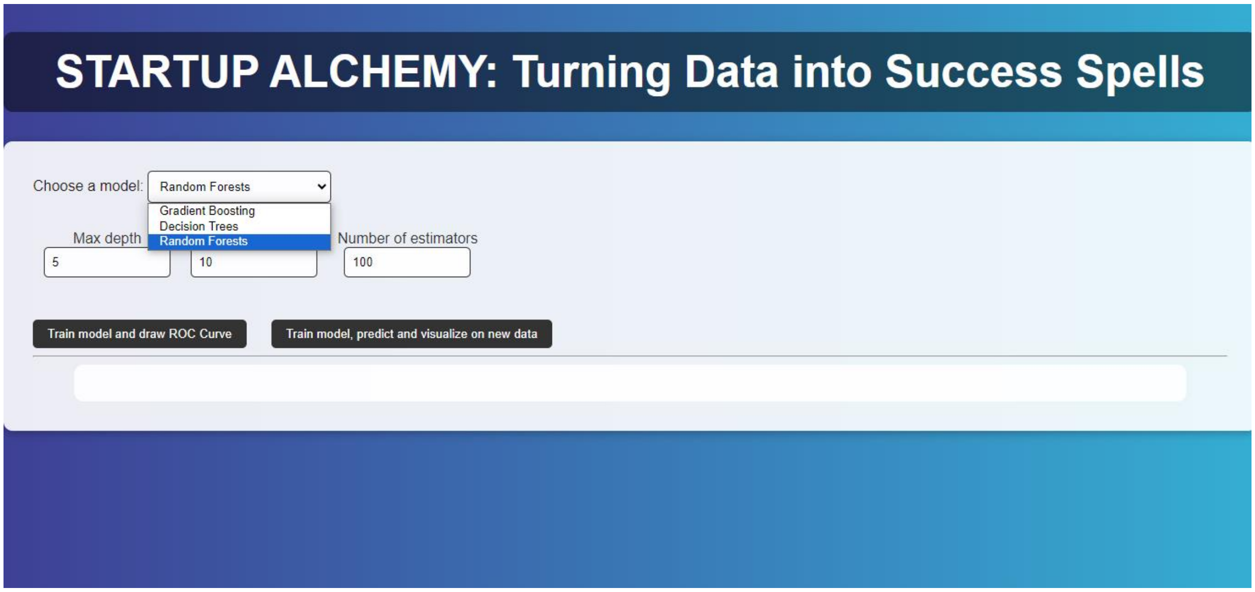
Choose a model: Decision Trees

Max depth 5

10

Gradient Boosting
Decision Trees
Random Forests
Train model and draw ROC Curve
Train model, predict and visualize on new data

Figure 4.8.8 Model 2



STARTUP ALCHEMY: Turning Data into Success Spells

Choose a model: Random Forests

Max depth 5

10

Number of estimators 100

Gradient Boosting
Decision Trees
Random Forests
Train model and draw ROC Curve
Train model, predict and visualize on new data

Figure 4.8.9 Model 3

ROC Curve Analysis:

The ROC curve analysis showcased the robust performance of our machine learning models. Each model—Gradient Boosting, Random Forest, and Decision Trees—exhibited commendable predictive accuracy. The curves visually convey the trade-offs between true positive rates and false positive rates, allowing for a nuanced assessment of model performance. The area under the ROC curve (AUC-ROC) metrics further underscore the efficacy of our predictive models.

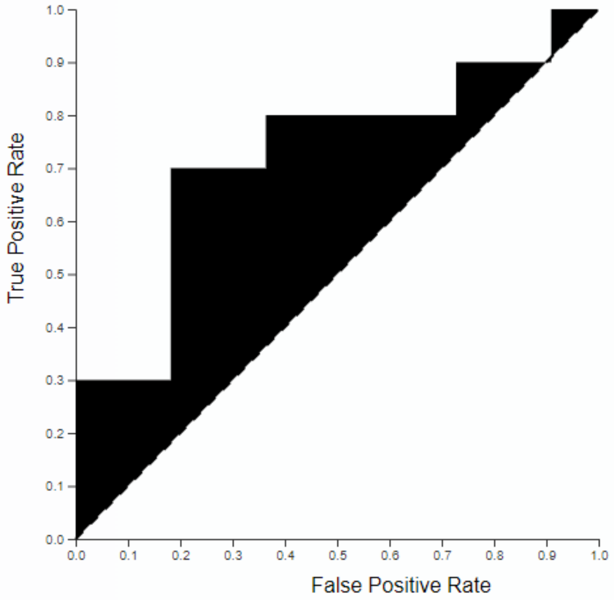


Figure 4.8.10 ROC Curve 1

(Gradient Boosting Model)

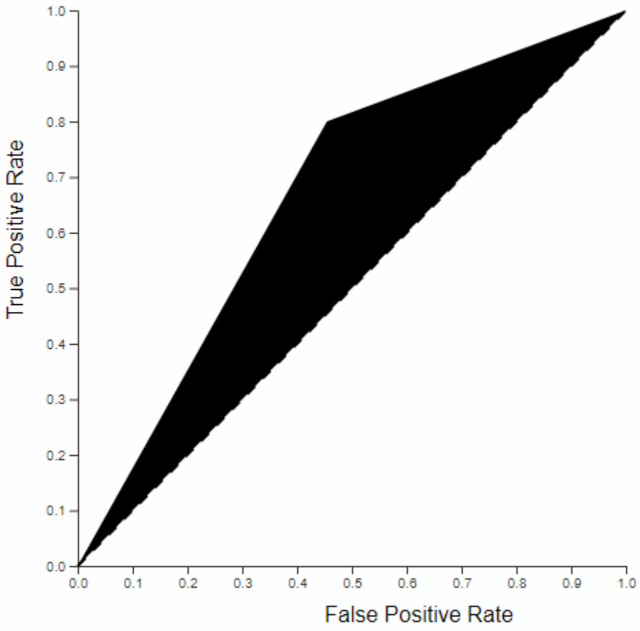


Figure 4.8.11 ROC Curve 2

(Decision Tree Model)

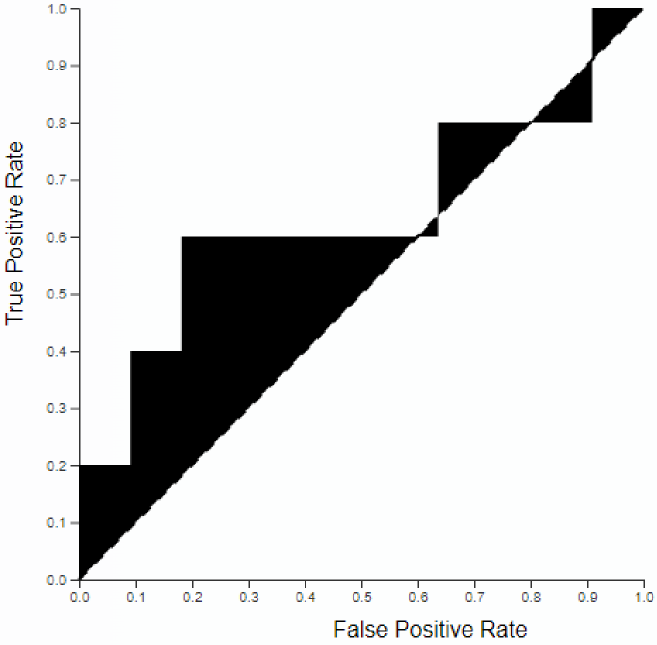
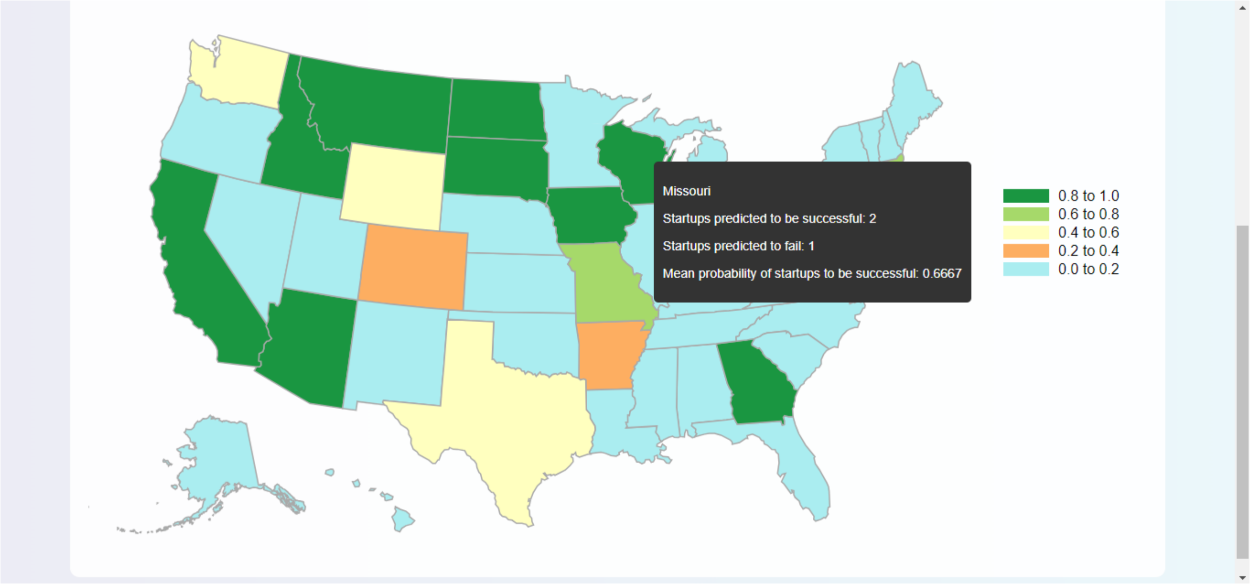


Figure 4.8.12 ROC Curve 3

(Random Forests Model)

Geospatial Visualization on US Map:

Our project's geospatial visualization component presents a captivating portrayal of startup success across different U.S. states. The map vividly displays the distribution of successful and unsuccessful startups, with varying colors indicating the magnitude of each category. This visual representation enables stakeholders to glean valuable insights into regional trends, aiding strategic decision-making in the dynamic landscape of startup entrepreneurship.



Missouri

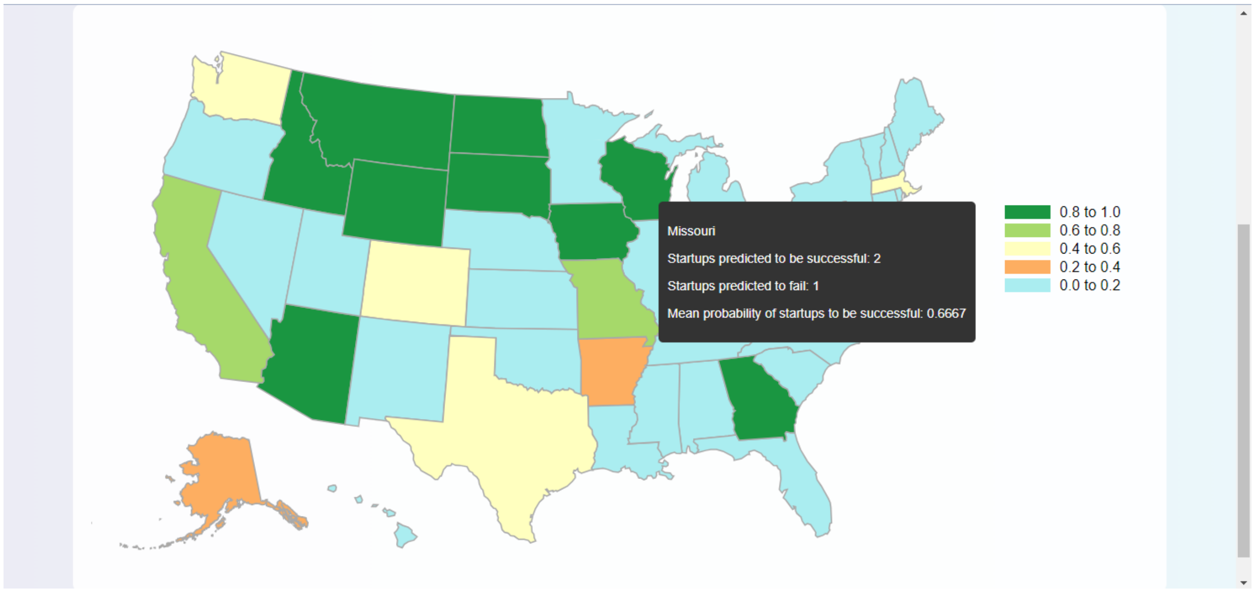
Startups predicted to be successful: 2

Startups predicted to fail: 1

Mean probability of startups to be successful: 0.6667

Figure 4.8.13 Geospatial Visualization 1

(Gradient Boosting Algorithm)



Missouri

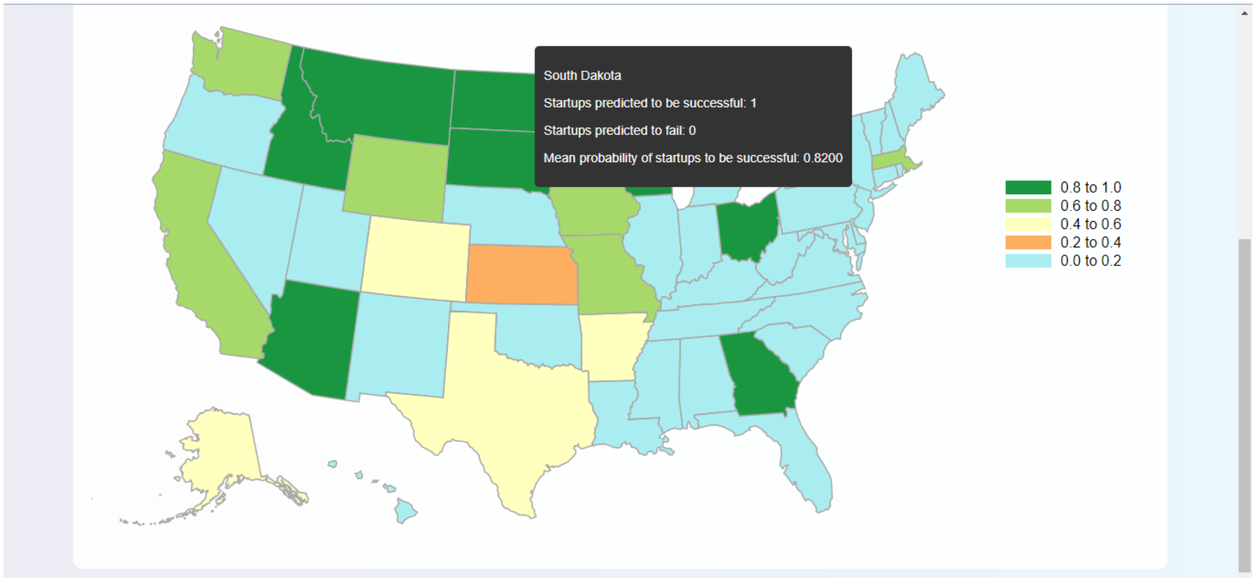
Startups predicted to be successful: 2

Startups predicted to fail: 1

Mean probability of startups to be successful: 0.6667

Figure 4.8.14 Geospatial Visualization 2

(Decision Trees Algorithm)



South Dakota

Startups predicted to be successful: 1

Startups predicted to fail: 0

Mean probability of startups to be successful: 0.8200

Figure 4.8.15 Geospatial Visualization 3

(Random Forests Algorithm)

4.9 CONCLUSION

In conclusion, "Startup Alchemy: Turning Data into Success Spells" represents a significant leap forward in leveraging data and artificial intelligence for predicting the success of startups, with a specialized focus on AI startups in healthcare. Through the simultaneous training of Gradient Boosting, Random Forest, and Decision Tree Classifier models, our project introduces a robust and diverse approach to predictive analytics in the dynamic landscape of startup ecosystems. The benefits of model diversity and ensemble learning enhance the overall predictive accuracy, offering stakeholders nuanced insights into the factors influencing startup success.

The creation of a bespoke dataset and its meticulous curation, alongside the application of advanced visualization techniques, provides an intuitive exploration of data relationships. The use of Python's Matplotlib library for visualization, along with other JavaScript libraries for frontend interactivity, ensures a comprehensive understanding of influential features for model training. The project's outcomes are not only confined to predictive accuracy but also extend to an informed feature selection process that can guide strategic decision-making.

Looking ahead, the project's future scope includes further refinement of models, incorporating more sophisticated algorithms and expanding the dataset to encompass a broader spectrum of startup attributes. The deployment of machine learning models on real-time data and continuous monitoring of their performance can contribute to an adaptive and evolving predictive system. Additionally, integrating user feedback and refining the user interface can enhance the project's usability and accessibility for a wider audience.

In conclusion, "Startup Alchemy" lays the foundation for informed decision-making in the startup landscape, providing a transformative tool for entrepreneurs, investors, and decision-makers. The amalgamation of data science, artificial intelligence, and advanced visualization techniques creates a powerful synergy, unlocking insights that can potentially shape the future trajectory of startups, particularly in the burgeoning field of AI in healthcare. As we reflect on the journey of transforming raw data into predictive spells, the project stands as a testament to the potential of data-driven innovation in the entrepreneurial realm.

5. REFERENCES

Following published works and sites were referred that helped us complete this project :

1. Research Papers and Thesis:

- **"Predicting Startup Success Using Publicly Available Data"** by Emily Gavrilenko, A Thesis presented to the Faculty of California Polytechnic State University, San Luis Obispo.
- **"Predicting the outcome of startups: less failure, more success"** by Krishna, A., Agrawal, A., & Choudhary, A. (2016, December). In *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)* (pp. 798-805). IEEE.
- **"Next-generation business models for artificial intelligence start-ups in the healthcare industry."** by Kulkov, Ignat. *International Journal of Entrepreneurial Behavior & Research* 29.4 (2023): 860-885.

2. Data Sources:

- Crunchbase: www.crunchbase.com
- Kaggle: www.kaggle.com
- Medical Startups: https://www.medicalstartups.org/top/ai/

3. Learning Sources:

- GitHub: www.github.com
- YouTube: www.youtube.com
- W3Schools: www.w3schools.com
- Scikit Learn: www.scikit-learn.org