US Restaurant Survival Web Application

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Introduction: During the COVID-19 pandemic, many restaurants were forced to temporarily or permanently close, providing new opportunities for emerging entrepreneurs and prospective restaurant owners. However, whether before or during the pandemic, establishing restaurants at locations that are optimal for revenue generation continues to be a pain point. Even though prospective restaurant owners are taking more of a data-driven approach to determining where to open restaurants, they lack the ability to synthesize across multiple data points, instead relying on intuition and "experience".

Problem: While there are more data-savvy restaurant owners today, many of them are still foreign to leveraging integrated data to make key decisions. There is also a lack of industrialized tools for this industry due to the vast number of factors contributing to restaurant success. There is a vast amount of data that can be analyzed, but the more difficult challenge is understanding how data relates to each other and how to make sense of the data to make decisions to minimize the probability of failure.

Literature Survey: The QuaFoodies' team examined multiple sources (below) to help inform our solution. The articles below contain research that provides evidence for the above problem and supports the ideas and decisions made in our proposed method.

Calculating restaurant failure rates using longitudinal census data: This paper attempts to debunk the myth that nine out of ten restaurants fail in their first year. The research shows that only about 15% of restaurants fail after one year in business, which supports our project idea that if the strategy and operation is well planned, there is a good potential for restaurants to prevent closure. Data is limited to the Irish food sector. (Healy & Mac, 2018)

Craving success: Introduction to critical success factors ....: This paper identifies critical success factors in the Irish restaurant industry. This paper is useful, because like what we did, it identifies factors important for restaurant viability; that helped inform the factors we used in this project. However, this paper was written before the pandemic and does not consider COVID-19. (Healy, 2014)

Developing an indicative model….: This study discusses a model for preserving restaurant viability during COVID-19 and uses interviews from 50 restaurant owners in Taiwan. This study is useful, because it brings up the importance of external factors in restaurant viability, which is what we also did. However, the factors in their model are abstract (an example is Support), and we used something more concrete. (Gkoumas, 2021)

Hospitality business longevity under COVID-19….: This study explores the impact COVID-19 has on New Zealand restaurants, cafes, and takeaway food outlets via online surveys taken by 11 senior industry executives. This study is useful because it is an example of evaluating COVID-19's impact on business longevity. Its approach, however, is limited in that it relies on thoughts from industry executives. (Neill & Hemmington, 2021)

The Impact of the COVID-19 Pandemic on Occupational Stress….: The study discussed in this paper investigates the impact COVID-19 has on restaurant and food service workers via interviews and thematic analysis. This study is useful because its findings prove the relevance of our project. However, while this study focuses primarily on restaurant workers, our project aims to address broader audience. (Kriebel, Furnari & Lippert, 2021)

Predicting Global Restaurant Facility Closures: This paper shows that restaurant closures can be predicted using purely online review data from Yelp. The author noted that to increase model precision, data such as rent, demographic and psychographic data should be included, which is what we did as well. (Snow, 2018)

Independent restaurant operator perspectives in the wake of the COVID-19 pandemic: This paper explores thoughts of South Carolina restaurant operators in Spring 2020. In this study, 65% of them felt that their restaurants could not stay open if COVID-19 related restrictions remained in-place until 2021. This study is useful because it illustrates who could benefit from our proposed project. A shortcoming was that it was only aimed at restaurant owners, and we tend to help other members of the economy as well. (Brizek, Frash, McLeod & Patience, 2021)

Why Restaurants Fail? Part V….: This paper is useful for our project because it confirms our initial idea of incorporating factors such as location, type of cuisine, and health code violations, as features to predict restaurant survival. A shortcoming is that analysis was conducted pre-pandemic. (Parsa,Lamb & Xie, 2019)

Reimagining European restaurants for the next normal: This paper examines success factors that restaurants should focus on to do well in the "next normal". This is useful because it is relevant to our topic and highlights factors such as focusing on digital and enhancing delivery capabilities, which have increased importance due to COVID-19. A shortcoming was a lack of detailed data to support building a predictive model. (Khan & Youldon, 2020)

The impact of COVID-19 on small business owners: Evidence from the first 3 months after widespread social-distancing restrictions: This paper explores the relationship between small business closures and discriminating features of business owners, e.g. race and gender. This is notable when we considered feature selection for our models. A shortcoming is it doesn't go into detail of a particular industry and thus does not consider more granular features specific to predicting success or failure. (Farlie, 2020)

Small Business Survival Capabilities...: This paper examines the functional relationship between revenue resiliency, labor costs, and committed costs in determining business success. This is important in helping us decide whether to focus on the United States at large or a particular city. The shortcoming is the extrapolation to regions outside of the locale where the data is sourced (Bartlett, 2020)

Restaurants' Rating Prediction Using Yelp Dataset: This paper explains the modelling step and output analysis from predicting restaurant ratings using Yelp data. It was helpful in helping us build models integrating Yelp data with other data sources. A shortcoming is that it only leveraged Yelp data. (Chen, 2020)

Sentiment Analysis of Yelp's Ratings Based on Text Reviews: This research conducted a sentiment analysis of restaurant Yelp ratings based on text review. This research is not as useful as the other literature surveys since it conducted its analysis using review text only, which can be considered a shortcoming as well. We leveraged the key learnings from this text analysis and incorporated it with the other components of our analysis. (Xu, 2019)

Entrepreneurship and crime: The case of new restaurant location decisions: This study is relevant as authors used crimes as factors to build a regression model to examine the relationship between crime and restaurant openings. Similarly, we used non-restaurant public data to build predictive models related to restaurants. A shortcoming is that the study only looked at correlation and not at prediction. (Sloan, Caudill, Mixon Jr, 2015)

Finance and Economics Discussion Series: This paper discusses traditional and non-traditional data sources used to measure business closures as well as the difficulty in distinguishing between temporary and permanent closure. It provided insight into potential data sources for our analysis and guidance on proper use. A shortcoming is that it looks at broader industries than just the restaurant industry. (Crane, 2020)

Exploring Visualization Implementation Challenges Faced by D3 Users Online: In building anything it is important to understand the limitations, and benefits of your tooling, so articles, such as this article, that help explore different libraries and approaches in building data visualization software seemed fitting. A shortcoming is it does not state challenges specific to the visualizations we plan to build. (Battle, 2021)

To Type or Not to Type: Quantifying Detectable Bugs in JavaScript: Typescript helps reduce the number of bugs in code according to the research outlined in this article that measured how many bugs were caught by the statically typed language. Browser based languages are very useful and common in data visualization. It's great to have evidence that tools you're choosing are beneficial and create an overall better product. A shortcoming is that it doesn't cover how to identify bugs in Typescript when working with React based visualization libraries. (Gao, 2017)

Can Online Consumer Reviews Signal Restaurant Closure…: This research attempts to predict business closure using online consumer reviews through deep learning and time-series techniques. This was useful because it provides details to the modelling steps in which our project team benefited from using as a modelling framework. One of the shortcomings of this research is that it did not consider other micro or macro-economic factors. (Tao & Zhou, 2020)

Proposed Method

The QuaFoodies' Solution: The QuaFoodies' solution provides an innovative approach at addressing restaurant survivability by integrating data across multiple sources, particularly COVID-19 data, and providing data-driven analysis of factors that contribute to the success of a newly opened restaurant. Our approach is timely and relevant due to the social, economic, and health-related challenges that the COVID-19 pandemic brought to the food and hospitality industry. Our team anticipates that the QuaFoodies' solution can provide aid and positive outcomes to individual restaurant owners as well as local economies with decisions related to location and operational strategy, resulting in successful business openings and survival.

<u>Considerations and Risks:</u> Given the limitations due to this solution being completed for a course project, there were no monetary costs, and was completed within the timeframe of the course. Risks to success primarily revolved around access to a sufficient volume of accurate data, such as restaurant revenue and foot traffic.

<u>Technical Approach</u>: The QuaFoodies' team has created a web application that has the following innovative features to allow prospective restaurant owners, curious residents, and local policymakers to infer conclusions and make decisions about restaurant survivability across the United States or in their own cities:

1. Choropleth map of restaurant closures and restaurants that stayed open across the continental US since the COVID-19 pandemic has begun (Figure 1).
    - Unlike previous work that has been done in understanding the relationship between restaurant viability and the COVID-19 pandemic, such as in the "Independent restaurant operator perspectives in the wake of the COVID-19 pandemic" research paper which limited its scope to the State of South Carolina, this feature is innovative as it provides a nationwide view.
2. Ability to take user input of potential features of prospective restaurant to obtain the probability of the restaurant's survival in the chosen location (Figure 2).
    - This feature is innovative as there is currently NO integrated solution/app in the market that easily outputs restaurant survivability based on a set of provided inputs. Currently these inputs are individually researched and sourced from several sites, data sources and articles by prospective restaurant owners.
3. The predictive model used to estimate the probability of the restaurant closing is built from a well-integrated dataset using current social, economic, and restaurant information, and was selected as the final model via performance comparison among several different analytical models.
    - This approach is innovative as there is no other previous research on restaurant survivability using a classification model with as many different data sources as we had (especially COVID-19 data). In addition, there wasn't any other research specifically testing the XGBoost model for predicting restaurant survival.

The web app was created using Typescript and React framework. The app also leverages a data visualization library called nivo. The specific component used from the nivo library is the responsive choropleth map. The map takes a collection of Geo JSON features to create polygons in a browser DOM for visualization. Then, we supplied the component with the data that maps to the geo JSON ids in the feature set and provided color inputs to scale based on closings or openings per geographic location, which in our case was the lower 48 states. To consume the data, we integrated a csv parsing library that reads from a file and parses it to JSON. The JSON is then passed into the component after some data manipulation.

The component in our web app for user input was built using the React Material-UI component library. After the user submits their inputs, the app will make a call to the back-end python API, built using the Flask micro web framework, which processes the request JSON, enriching it with additional economic and health data for that zip code for final input into the model. For the purposes of this project, the API is hosted locally. The API inputs the final feature set for prediction to the champion predictive model, an XGBoost model (details in Model Evaluation section below), which is stored as a serialized Pickle object. The API returns a JSON object containing the model prediction for display within our UI, using some of the components from the nivo library. The response is a simple yet powerful one, namely, will your restaurant succeed or fail given the current trends in the industry during the covid-19 pandemic?

Figure 1. Choropleth maps in QuaFoodies' Web Application

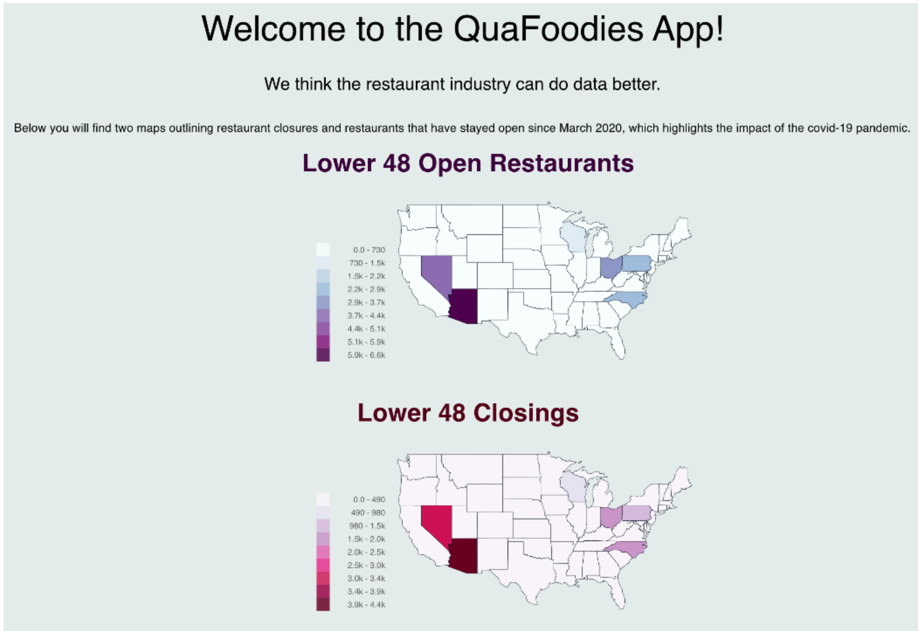
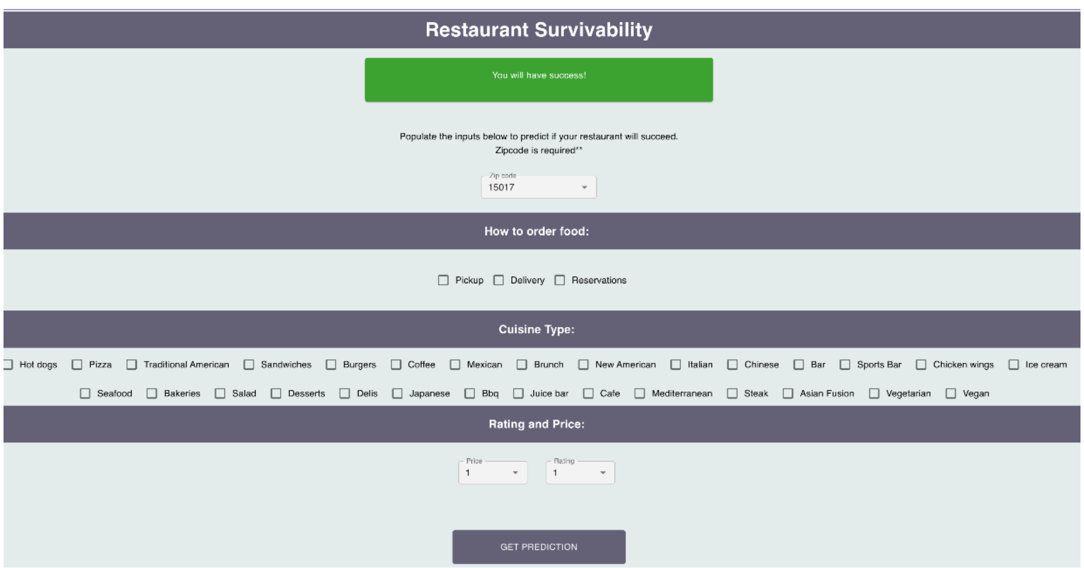


Figure 2. User Input Functionality in QuaFoodies' Web Application



<u>Data:</u> The data used by the web app is in csv format; these csv files are parsed and input into the choropleth map component via JSON. No issues relating to scaling or performance were experienced, thus we did not host the data in a PostgreSQL database as originally planned.

The main dataset we worked with was sourced from Yelp's open dataset, containing over 100,000 business ids from March 2020. To get current business information, including open/closed classification, we developed a Python script to pull data from the Yelp Fusion API. Due to an API key limitation of 5000 calls per day, data was pulled throughout March 2022. These records were then filtered to include only restaurants from the United States. Another script was developed to clean the data and create additional indicator/categorical columns. Datapoints with missing attributes were removed, and columns including but not limited to cuisines, price, and delivery were created. After filtering and cleaning the data, we were left with 34,118 datapoints from Yelp. Note that we were limited to the business ids from

March 2020 as the Yelp Fusion API offers no way to explicitly search for closed businesses. If we were to search for other businesses via the Yelp Fusion API, it is likely that only open restaurants would be returned and thus skew our data.

To build our predictive models, the Yelp data was then integrated with variables from several different data sources, namely, real estate rental price data from Zillow and Redfin (e.g. rental price, keyed on month and zip code), COVID-19 transmission rate data from the CDC (e.g. number of cases and vaccination rate, keyed on FIPS code), and the Unemployment Report from USDA (e.g. unemployment rate and median household income, keyed off of FIPS code). All datasets were keyed off zip code, FIPS code, or state, which was used to join and build our feature set. We leveraged similar data cleansing and feature engineering methods as with the Yelp dataset for use in predictive modeling. Our final dataset used for predictive model input had over 31,000 observations and 48 data attributes, excluding location variables.

Predictive Modeling: Our predictive modeling task completely leveraged Python and could be broken up into two major steps. The first step was data preprocessing and feature engineering. Using the integrated dataset, we started with exploratory and distribution analysis to further understand the predictor and target variables. We then conducted outlier analysis to identify potential outliers and apply needed treatment of these records as necessary. Then we conducted various statistical analysis to verify that modelling assumptions such as normality and others are satisfied. We anticipated that our variables would be highly correlated, so we also tested for multi-collinearity. Lastly, we ran through a few variable selection methods to decide the final set of variables or features we fed into the model.

The second major step was the model building and model evaluation process. We first split our final dataset into three buckets. Seventy percent of the data was allocated into the training dataset, used to train the model, and fit the parameters to the model. Fifteen percent of the data was allocated to the validation dataset, used to tune model hyperparameters and select the best models to proceed forward with. The remaining fifteen percent of the data was allocated to the test dataset and used to provide unbiased model performance evaluation. We then trained the following classification models: logistic regression, decision tree, random forest, Naïve Bayes, and XGBoost. We then conducted model evaluation and model tuning to optimize the model hyperparameters to select the best performing model for prediction.

Experiments and Evaluation

To ensure that our solution was sufficiently addressing the problem we looked at the following questions:

1. Data Attribute Evaluation: Are the data attributes leveraged from multiple sources relevant in determining restaurant closure?
2. Model Evaluation: Does our model predict restaurant closure accurately?
3. Scalability Evaluation: Is our web application able to handle different volumes of data and still operate as expected?
4. User Testing Evaluation: Does the web application correctly accept user inputs? Do users find the application intuitive and easy to use?

Data Attribute Evaluation: To answer the question in determining a final set of data attributes that were both across different sources and relevant in determining restaurant closure, we conducted data profiling on all the variables. This helped us determine which variables were highly correlated with each other as well as might not be so relevant. For example, during our data profiling we found that indicator variables such as moderate and substantial COVID-19 transmission, urban influence code and rural urban continuum code were highly correlated with each other, and thus some could be removed from our final set of data attributes.

Model Evaluation: As mentioned in the predictive modeling section of this paper, we tested a variety of different classification models using different hyperparameters to select the champion model for our solution. We used several key model evaluation methods and metrics to evaluate and compare the classification models, including a confusion matrix, area under the curve (AUC), and accuracy scores. The confusion matrix was helpful in keeping track of model predicted output compared to actual values and allowed us to compare models on various performance metrics such as accuracy, sensitivity, specificity, precision, and F1 score. We primarily focused on F1 score as the metric from the confusion matrix as it is the most balanced metric between sensitivity and precision. AUC and accuracy scores also provided a quick and easy, industry-accepted metric to compare the models. Our results are shown in the below table.

Table 1. Classification Model Evaluation Results

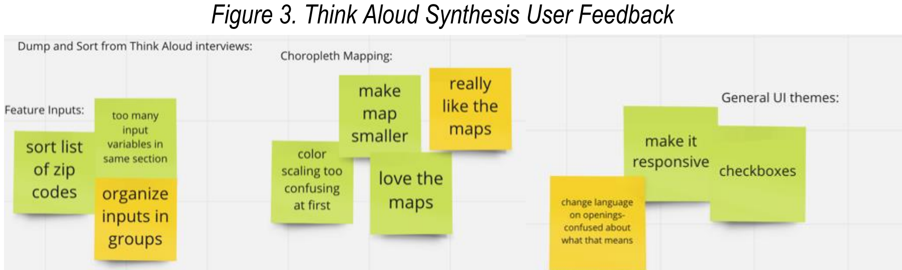
Model	Accuracy	f1-score (not closed)	f1-score (closed)	AUC
Logistic Regression	60.0%	0.74	0.11	51.0%
Decision Tree	74.4%	0.80	0.66	72.2%
Random Forest	75.2%	0.81	0.66	72.6%
Naïve Bayes	60.3%	0.73	0.22	52.8%
XGBoost	75.9%	0.81	0.67	73.3%

From the above tests, we were able to determine that aside from the logistic regression and naïve bayes model, all other models predicted with above 70% accuracy and the XGBoost model performed the best. These tests were able to help us conclude the first experiment question: the champion model we selected predicts restaurant closure with sufficient accuracy.

Scalability: The construction of the web app and predictive model was first built on a subset of our entire data. As mentioned above in the data piece, this subset was stored as csv files. As additional data was retrieved from Yelp, we added the new data to the existing csv, re-validated our model selection and tested non-functional performance requirements and functional requirements of our web app and underlying API (e.g., response time < 1 second from user input to result and that the user input yields expected prediction of open/close based, respectively).

User Testing: One test we performed with family that was low budget and highly effective is called "think aloud protocol". This user testing strategy involved someone sitting down with us for 30 or so minutes while we recorded them talking out loud as they used our application. This helped us gather unbiased feedback, first impressions, and assumptions the user was making given our visualizations and UI interface. We then synthesized the results using a method called "dump and sort" where we dump the feedback and sort it to find themes/categories that helped us improve the quality and usability of our app. Optimally, we would want prospective users across the US to be able to provide feedback on the app, however due to the limitation of this class, that was not possible in our given timeframe. Below is a screenshot of our think aloud synthesis, which we analyzed using the dump and sort method:

Figure 3. Think Aloud Synthesis User Feedback



Conclusion and Discussion: All team members contributed a similar amount of effort in the creation of this web application. Given that this solution was created for a group project and had limitations set by our given timeframe, there are still areas of the web application that could be improved to create a more marketable product. For example, expanding the amount of zip codes in our database, allowing users to search by county or state via the choropleth map, outputting the probability of closure instead of a straight answer, and giving users more information such as characteristics of restaurants that are most successful in their chosen location.

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