Senior Design Project

Bat Lab
Vision and Scope

Version 1.5

Revision History

Date	Version	Description	Author
15/Sep/2025	1.0	Pre-Client Meeting Draft	GROUP
19/Sep/2025	1.1	Delegated Sections Draft	GROUP
22/Sep/2025	1.2	Rough Draft	GROUP
26/Sep/2025	1.3	Rough Draft w/ Client Updates	GROUP
26/Sep/2025	1.4	Final Draft w/ Verbiage Update	Rachel Rajamoney
01/Apr/2026	1.5	Final Draft w/ Refined Scope	Stryder Schossberger

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Vision

1. Introduction

The purpose of this document is to collect, analyze, and define the business requirements, i.e., high-level needs, desired ultimate business outcomes and features of the Bat Lab. It focuses on the capabilities needed by the stakeholders and the target users, and why these need to exist in the first place. The details of how the Bat Lab fulfills these needs are detailed in the use-case and supplementary specifications.

1.1 Background

Bats exhibit niche partitioning in their echolocation call structure to reduce competition, often adjusting their calls to not interfere with other species flying in the same space. Subsequently, based on location, bats can produce slightly variating calls, detected through frequency, duration, and shape. These subtle differences make existing automated identification tools unreliable in region-specific contexts, forcing researchers to identify calls manually. The manual processing of bat calls is heavily time-consuming and places limits on the scope of ecological research. As a result, researchers are often forced to reduce the numbers of calls analyzed, which in turn limits the ability to study seasonal activity patterns, habitat use, and species interactions. An AI-driven machine learning tool would revolutionize the processing of bat calls by increasing efficiency, unlocking new possibilities for understanding species presence, behavioral patterns, resource use, and seasonal movements.

This project proposes the development of a machine learning tool that will support ecological research by automating the identification of bat echolocation calls.

1.2 References

Machine Learning Proposal for South African Bats Acoustics Final

2. Business Requirements

2.1 Business Opportunity/Problem Statement

The problem of	*manually classifying and identifying a significant number of bat calls*
affects	*researchers with large amounts of unclassified bat call data*
the impact of which is	*a high cost in time required for identification*
a successful solution would be	*a Machine Learning Model that would dramatically improve classifying and accurately identifying bats*

2.2 Business Objectives

BO-1: Identify bat species from acoustic recordings based on region-specific echolocation call features, recognize subtle variations or “accents” in call structure that are shaped by existing bat communities (i.e., the species present) unique to the Eastern Cape of South Africa.
BO-2: Extend the tool to classify bat behaviors from call sequences, including phases associated with commuting, searching for resources, approaching resource, drinking, and catching prey activities that inform broader ecological understanding of resource use, such as prey and water.
BO-3: Improve efficiency of current classification methods implemented by experts in the field of bat research and conservation.
BO-4: Provide an enhanced user experience than current industry standards and products used to identify bat species in specific calls.
BO-5: Develop a machine learning tool to support and provide data for ecological research.

2.3 Success Metrics

SM-1: The machine learning model uses call parameters (such as characteristic frequency, maximum frequency, minimum frequency, waveform etc.) to identify echolocation call pulses to species.
SM-2: This machine learning model accurately identifies species based on call structure, accounting for regional variation, from locally collected echolocation data.
SM-3: In the case the audio clip or potential identification is unclear, the model returns “Unknown,” thereby cutting down manual identification time by eliminating matched species and flagging corner cases.
SM-4: The model’s accuracy increases by learning from new data, ensuring that the model becomes increasingly robust and regionally accurate.
SM-5: The model is able to export a .xls file containing call parameter data from the imported audio files.

2.4 Vision Statement

For	academic researchers, conservation organizations, government agencies, national parks, and zoos
Who	need to rapidly and accurately identify bat species from acoustic recordings, without the time-consuming process of manual identification.
The (product name)	A Supervised Machine Learning Model for Bat Acoustic Identification, Bat Lab,

That	efficiently and accurately identifies bat species from acoustic recordings.
Unlike	existing bat call identification tools (such as SonoBat, Kaleidoscope, Anabat Insight, BatSound), which are limited by their call libraries, often misidentify species, and do not account for regional accents. These tools also struggle with recordings containing multiple bats, averaging calls together, producing unreliable results, and cannot identify behaviors (such as commuting, foraging, drinking).
Our product	● A trainable machine learning model that efficiently and accurately identifies bat species using audio shapes, patterns, frequencies, and regional accents. ● Confidently flags unknown or ambiguous calls for human review instead of using its own judgment to produce a false identification. ● Maintains a large, scalable, and continuously growing library of bat calls.

2.5 Business Risks

RI-1: Misclassification of bats can cause limitations in research activities, limiting seasonal learning opportunities and reducing efficiency. *(Probability = 0.1; Impact 9)*

A. *Mitigation Actions: Ensure the model accuracy by learning from new data, training on known calls, testing on unknown data, validating and correcting predictions, and incorporating new examples back into the training set, effectively confirming increasing accuracy.*
B. *Mitigation Actions: Ensure third party customer compliance with all Wildlife and Environmental Laws relating, on a local, state, national, and global level.*

RI-2: Misidentification of the presence of a certain species in a specific area can present ecological and conservation issues if species quantities and activities are inaccurately recorded. *(Probability = 0.15; Impact 9)*

A. *Mitigation Actions: Reference RI-1.A.*
B. *Mitigation Actions: Reference RI-1.B.*

RI-3: In the case of patenting this product, misclassification of certain species can result in a lawsuit in the case of misuse or misinterpretation of output by a third party customer. *(Probability = 0.1; Impact 9)*

A. *Mitigation Actions: Reference RI-1.A.*
B. *Mitigation Actions: Reference RI-1.B.*
C. *Mitigation Actions: List the machine learning model as Open Source*

RI-4: In the case of patenting this product, misclassification of bats can result in higher insurance premiums. *(Probability = 0.1; Impact 4)*

A. *Mitigation Actions: Reference RI-1.A.*
B. *Mitigation Actions: Reference RI-1.B.*

RI-5: In the case of patenting this product, misclassification of bats can lead to the revocation of third party customer permits to record data. *(Probability = 0.1; Impact 8)*

A. *Mitigation Actions: Reference RI-1.A.*
B. *Mitigation Actions: Reference RI-1.B.*

C. *Mitigation Actions: Reference RI-3.C.*

2.6 Business Assumptions and Dependencies

AS-1: This model is based upon the assumption that each bat species has a characteristic call shape and frequency range that can shift regionally.
AS-2: This model will use a supervised learning approach, leveraging a curated library of bat echolocation calls that have already been identified to species and activity type by experts.
AS-3: This model will follow a rule-based structure where the model "learns" what defines a call from Species A vs. Species B, or a foraging call vs. a drinking buzz.
AS-4: The client will be providing audio recordings of these bat echolocation calls, as well as known calls, to effectively train the model.

DE-1: This model must include the visualization of audio recordings, using existing or newly-built systems, as the client depends on these spectrograms to classify any unknown audio clips.
DE-2: The model depends on an external software, Sonobat, to clean the data extracted from the audio files.
DE-3: The model testing predictions will be checked and corrected by experts, thereby validating predictions.
DE-4: The client depends on this model to understand which species currently access the available resources in the East Cape and how this changes as the surrounding habitat improves.

3. Stakeholder Profiles and User Descriptions

3.1 Stakeholder Profiles

Stakeholder	Major value or benefit from this product	Attitudes	Major features of interest	Constraints	End user or not?
Bat researchers	Increased efficiency, as less time will be spent on manual identification. Correct identification will also contribute to understanding species presence, behavioral patterns, resource use, and seasonal movements.	Committed to a viable identification model, supportive of reducing manual workload.	Wants confident and correct identification of known species. Interested in a GUI that can simplify usage.	Researchers must be trained on how to use the model.	Yes

3.2 User Environment

The standard process of identifying bat calls is handled individually, but more than one person may be using the model at any given time. The responsibilities of this task may either be split up between these users, or accomplished by one person alone. The task cycle involves: installing a recorder in an area of interest to the researcher, collecting sound data over a specified time, and analyzing the data to determine the species of bats present. This data will be accessed through existing lab desktops and initially processed using a bat detector, which will produce .WAV file clips that are typically 3-4 seconds in length. These files are what will be used with the model to predict the bat species identification. The minimum working environment will consist of a machine learning model that will be used by the researcher to analyze a bat call and return a correct prediction for the species. The desirable working environment involves researchers interacting with this model using a graphical user interface (GUI) for an improved user experience. The GUI will have configurations for identification rules and use a localized call database.

3.3 Alternatives and Competition

The current competitors and alternatives of this machine learning model include SonoBat, Kaleidoscope, Anabat Insight, and Bat Sounds, and create a very timely process that requires a heavy manual workload. In this process, file clips from a bat detector get uploaded to SonoBat, which will scrub the data, meaning any noisy data is removed. Then, these output files would go to Kaleidoscope, which is a software designed to classify and cluster these files, and is able to export data from these calls into an excel file. After, for calls that are unable to be identified, these clips are run through SonoBat to produce a visual aid for classification, called a sonograph. However, these alternatives are not able to make this process automated, as Kaleidoscope and SonoBat have very limited databases that are not able to account for a majority of the current species. This leaves the rest for manual classification, which must be analyzed from sonographs, location, and data.

The current process, although lengthy and requiring a heavy manual workload, do have strengths. Namely, SonoBat allows users to focus on desired parts of the sonograph such as zooming in on various sections. In addition, the application can play the sound file at a frequency humans can hear, where speed and volume can also be adjusted. Kaleidoscope provides clustering based on frequencies to limit the possible range of identifiable species and aids in manual identification, such that only a few bat species within a small range are in consideration.

Weaknesses of the current process include being able to identify a limited number of species. In the context of the Eastern Cape of South Africa, there are 26 known bat species, with only 9 in the call library as possible options for identification on Kaleidoscope, severely limiting classification. Another weakness in these alternate processes include identification processes that can create unreliable predictions. The software averages the frequency of the bat call, which becomes an issue when the call is degraded (too far away, overlapping noise), or multiple species of bats are present within the same sound file. Additionally, frequency alone is not always sufficient to identify the bat species. Manual identification regularly relies on the shape of each bat call within a range of frequency, which is not leveraged in automated classification tools. Overall, the current process performs poorly in accurately classifying bats and is not considered reliable by stakeholders.

4. Scope and Limitations

4.1 Product Perspective

The machine learning tool is designed to automate the identification of bat echolocation calls and associated behaviors. It will be trained using a supervised learning approach, leveraging a curated library of calls already identified by experts to species and activity type. These calls will form the training dataset, establishing the baseline patterns, frequency ranges, and call structures associated with different species.

In the context of the Eastern Cape of South Africa, where over 26 bat species coexist, many species adjust their echolocation “accents” to avoid overlap with other bats. This regional variation makes existing automated tools less reliable. The proposed product addresses this by being trained on locally collected and classified data, allowing it to account for these variations and provide accurate, region specific identifications.

Kate Davis will collaborate and work closely with the team on this system in supplying labeled and organized call libraries based on known species and activity types. The model will learn rules based on parameters such as frequency (minimum, maximum, and characteristic), duration, slope, and call shape. Students will work with Kate Davis to train the model to recognize patterns, forming a rule based structure where the system learns distinctions between species calls.

After training, the model will be tested on datasets of unknown calls where predictions will be validated by experts, and any misclassified calls will be corrected and incorporated into the training library. This iterative cycle of training, testing, validation, and correction ensures the model becomes more robust over time.

Ultimately, this product identifies bat species with high accuracy, single out unidentifiable cases, and classifies behaviors from call sequences, thus reducing the manual workload required for acoustic analysis.

4.2 Major Features / Scope

FE-1: This model should be able to input .WAV audio files to identify bat species from acoustic recordings based on region-specific features.
FE-2: This model returns unidentifiable calls as “Unknown” to signal further manual identification.
FE-3: This model contains the features to export an Excel file to clients, providing parameter data.
FE-4: This model contains the ability to change the specific identification qualities to classify different species of bats, without overfitting sound files to a bat species.
FE-5: This system allows a multi-user environment.

4.3 Deployment Considerations

DC-1: It is emphasized that the client can access the software to update certain rules or create new ones in order to train the model.
DC-2: The model must allow input of audio files, in specific .wav files, to read, visualize, and classify the clips.
DC-3: The model should properly document and record usage logs.
DC-4: The model supports multiple users simultaneously.

5. Other Product Requirements

PR-1: The tool should not crash when handling noisy or low-quality calls. It should also flag incorrect predictions so that these can be reviewed and used to improve future training. The model should be designed to allow retraining as new data becomes available.
PR-2: A GUI is needed so that non-technical users (such as students or field researchers) can use the system easily. Users should also be able to adjust identification thresholds without needing to edit code.
PR-3: The program should run on standard Windows, Mac, or Linux desktops without requiring specialized hardware. It should be able to handle very large datasets.
PR-4: Data management should follow Texas Christian University’s research data policies, meaning files are stored securely, backed up, and documented. We also want to follow FAIR data principles (Findable, Accessible, Interoperable, Reusable) so that our dataset and results can be used by other researchers in the future.

