



Anomaly Detection for Smart Farming via Machine Learning

FINAL YEAR PROJECT S223/24
PANEL PRESENTATION

NAME : MUHAMMAD LUQMAN HAKIMI BIN MOHD ZIN
STUDENT ID : CS01081026
SUPERVISOR : ASSOC.PROF.TS.DR.ASMIDAR BTE ABU BAKAR
EXAMINER : TS.MARINA BTE MD. DIN



INTRODUCTION & BACKGROUND

Agriculture is one of important sector in economic growth, human rely on it to have their basic needs for sustainability. One of the branches of agriculture is aquaculture

Smart agriculture is the integration of agriculture with technology. To enhance human productivity, do complex tasks, and improve customer experiences.

The integration of technology (IoT) might possibly expose to cyber threats and disrupt daily operation of smart farming environment.

Many security mitigation applied to reduce the potential cyber security risk in IoT, one of it by using machine learning algorithms.



Agriculture

the science of cultivating the soil, and raising livestock in order to produce product.



Aquaculture

One of agriculture branches, focus on aquatic production either plants or animals



Internet-of-Things (IoT)

Use of technology to enhance productivity, and efficiency



Security Issues

IoT employs wireless connections, easy target for any attacks. Able to disrupt smart environment operation

PROBLEM STATEMENT

Context

Smart farming in aquaculture uses IoT for precise monitoring and management. Environmental factors like pH, temperature and turbidity is crucial for development of aquatic animals or plants.

Challenge

- IoT can possibly be exposed to cyber threats or inadvertent threats.
- Some studies have demonstrated potential anomaly identifications like (**Moso et al, 2021**), (**Catalano et al., 2022**), and (**Petkovski & Shehu,.2023**), but still lack of research about anomaly detection algorithm on smart aquaculture.



RESEARCH QUESTION



Which machine learning algorithms are best for detecting anomalies in smart aquaculture systems?



How do they compare in terms of characteristics and performance metrics?



How effective is the selected machine learning model for anomaly detection?



PROJECT OBJECTIVE

To review and identify suitable machine learning algorithms for anomaly detection in smart farming focusing on smart Aquaculture.

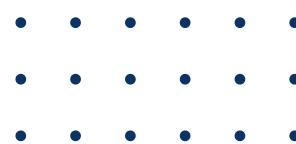
To conduct comparative analysis of machine learning algorithms.

To analyze result from the selected machine learning model.

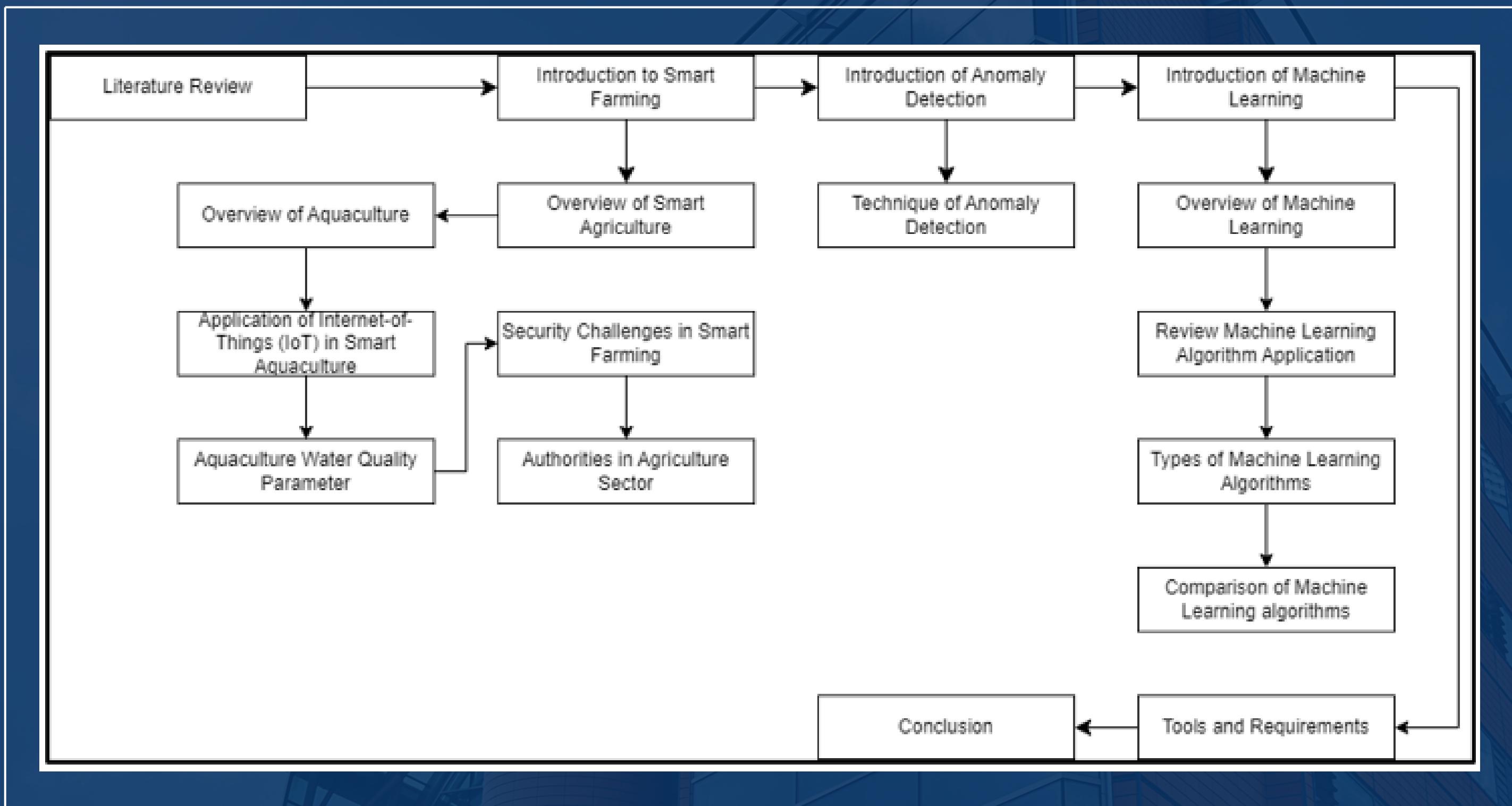
Research Scope



Review and identify machine learning algorithms used for anomaly detection and conduct proof-of-concept to analyze selected algorithm with the used of Smart Aquaculture dataset.



LITERATURE REVIEW



- Using technology to enhance farmer productivity
- “Zero-hunger” in SDGs
- Implementation of IoT and Machine Learning.



Overview of Smart Farming



Overview of Smart Aquaculture

- Raising aquatic creatures under regulated environments (pH, Temperature)
- Help farmer to do complex tasks classify fish species (Islam et al., 2021).
- Adaptation of climate change

SECURITY CHALLENGE IN SMART FARMING



Social Engineering

Malicious activity can be accomplished through human interaction.



False Data Injections

When injection happen, it could lead to excessive damage to aquatic lives.

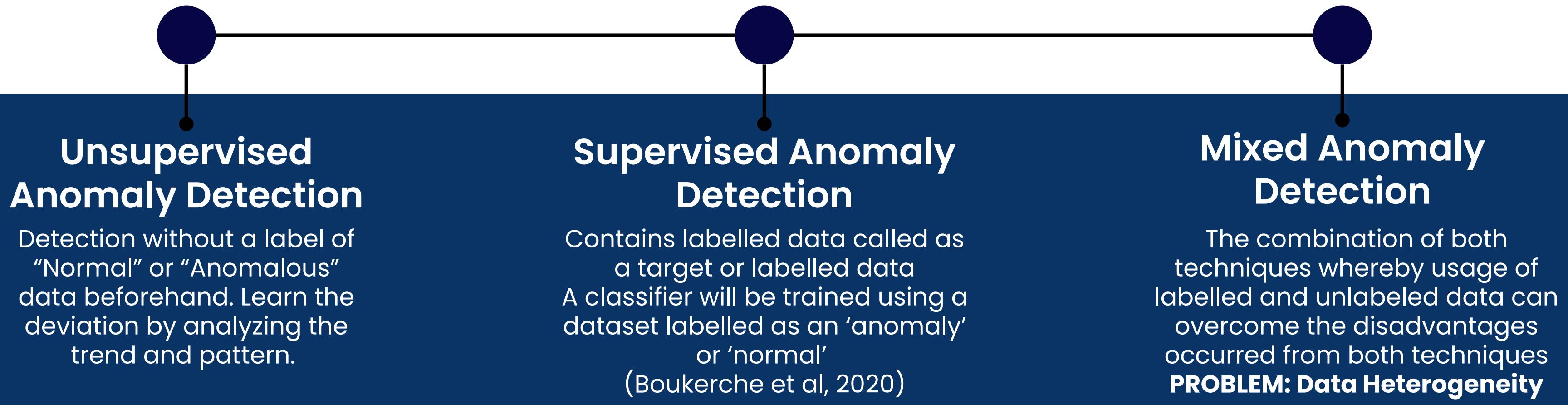


Malware Injection Attack

Malware might disrupt the process, and could possibly spread to other host.

Introduction Anomaly Detection

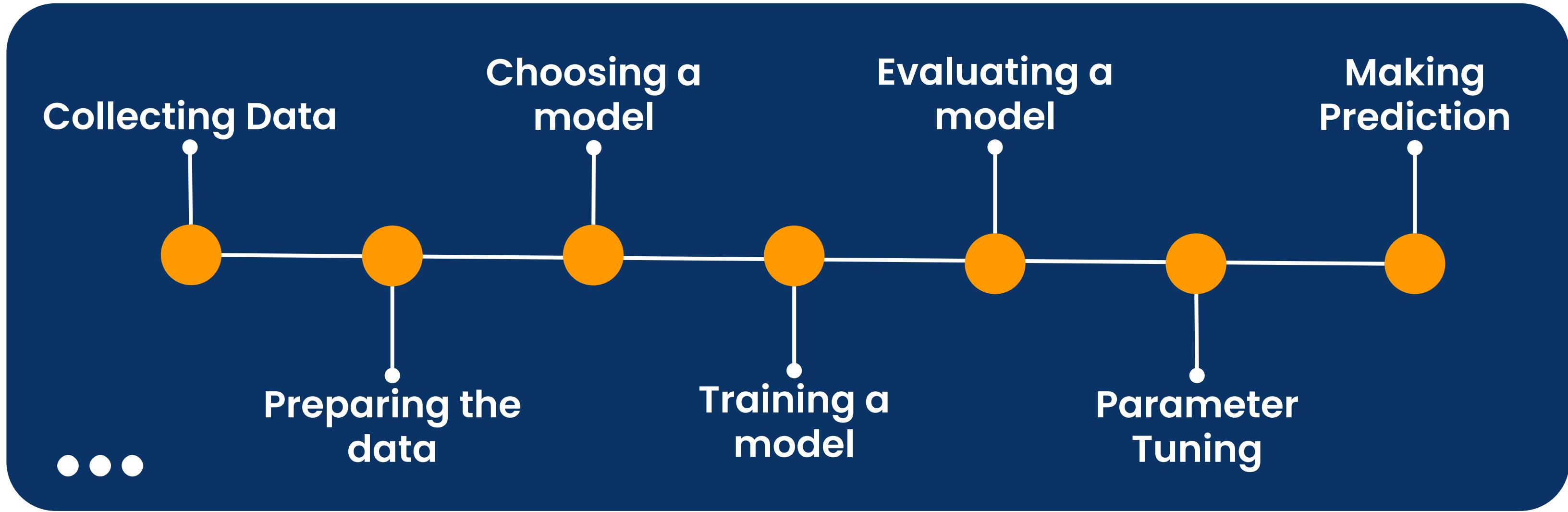
Anomaly refers to an observation of the values that differs from most of the normal values.



Introduction Machine Learning

Computer intelligence to help human to do complicated tasks with the use of algorithms.

OVERVIEW OF MACHINE LEARNING



Review Machine Learning Algorithm Application

TABLE 1. 1: Simplified literature review on machine learning application

Study	Approach	Proposed Method	Dataset	Performance Metrics	Significant Test
(Primartha & Tama, 2017)	Anomaly Detection	Random Forest	NSL-KDD, UNSW-NB15, and GPRS	Accuracy, False Alarm Rate	Yes
(N. Elmrabit et al, 2020)	Anomaly Detection	Logistic Regression (LR), Gaussian Naive Bayes (GNB), K-nearest neighbour (KNN), Decision Tree (DT), Adaptive Boosting (AdaB), Random Forest (RF), Convolutional Neural Network (CNN), Long Short-term memory (LSTM), Gated Recurrent Units (GRU), Simple Recurrent Neural Network (RNN), Deep Neural Network (DNN)	CICIDS-2017, UNSW-NB15, and Industrial Control System (ICS) cyber-attack datasets	Accuracy, precision, Recall, and AUC	Yes

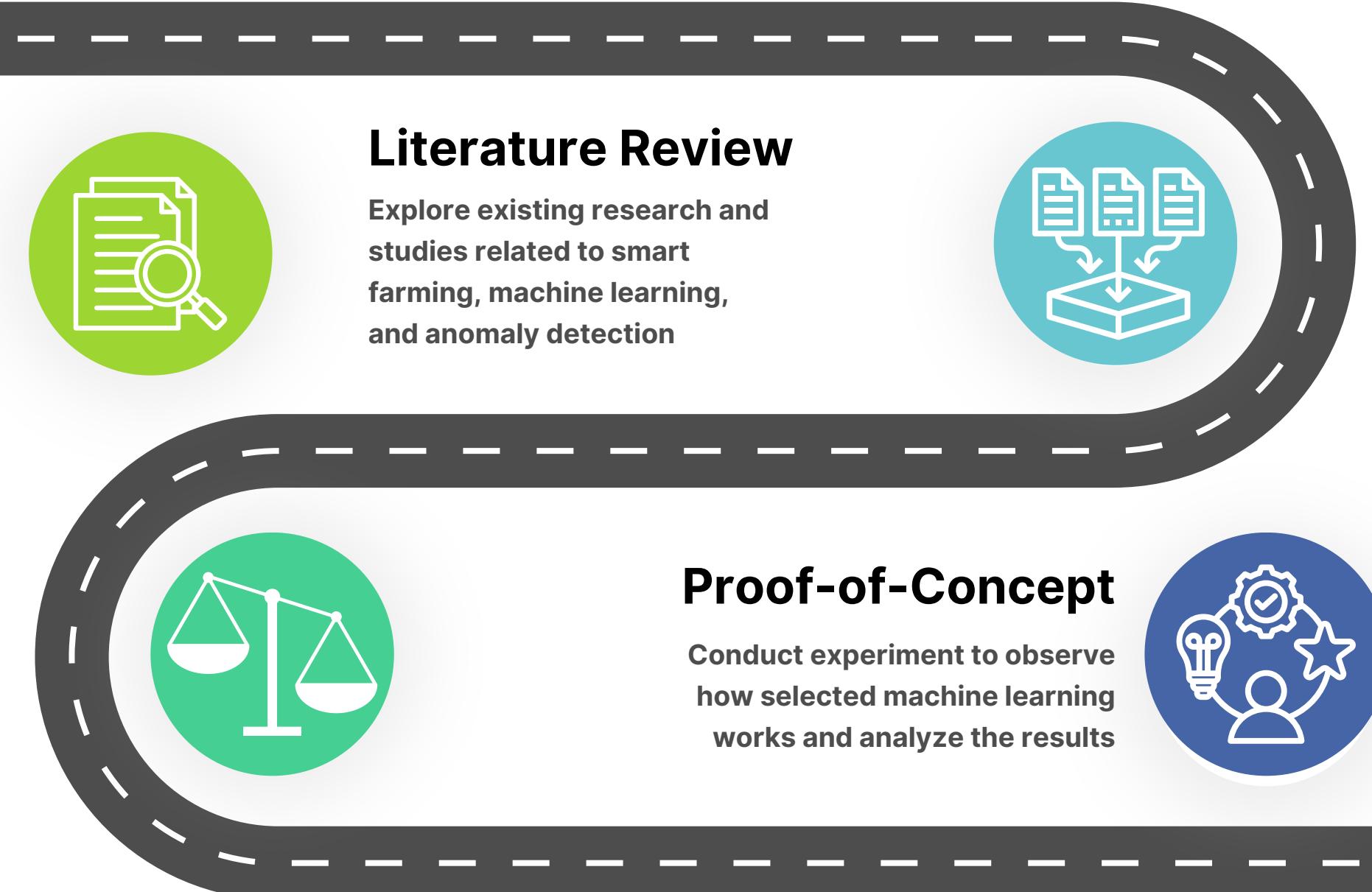
(Catalano et al., 2022)	Anomaly Detection	Multivariate Linear Regression (MLR) and Long Short-term Memory (LSTM)	Agriculture time-series dataset	Min Squared Error (MSE)	Yes
(Liu et al., 2008)	Anomaly Detection	Isolation Forest	http (KDDCUP99) and ForestCover dataset	AUC	Yes
(Islam et al., 2021)	Fish Survival Prediction	Random Forest	Aquaculture dataset (Real-time fish data)	Accuracy, True Positive (TP) rate and Kappa statistics	No
Hu et al. (2019)	Water Quality Prediction	Long Short-term Memory (LSTM)	Aquaculture dataset from designated sensor	Accuracy, Time cost	No
Petkovski & Shehu, (2023)	Anomaly Detection	K-means, Isolation Forest, Local Outlier Factor	Real-time time-series aquaculture dataset	Accuracy, Precision, Recall, and F-score	Yes
Ramteke & Monali Y., (2012)	Anomaly Detection	K-nearest neighbour (KNN)	CT scan images of normal and abnormal.	Sensitivity, Specificity, and Accuracy	Yes

Research Methodology

Comparative Analysis

Compare reviewed machine learning by conducting comparative analysis

Chapter: Analysis



DATA ACQUISITION

DATASET EXPLANATIONS

01

Description

- 1.Acquire from Kaggle
- 2.Created by Researcher in Dhaka University.
- 3.Consist of 591 data

02

Feature

- 1.pH Value
- 2.Temperature
- 3.Turbidity
- 4.11 Fish Species

03

Data Pre-processing

- 1.Filter fish species
- 2.Inject anomalies
- 3.Train Test Split (70:30)

pH	Temperature	Turbidity	Fish
6	27	4	katla
7.6	28	5.9	sing
7.8	27	5.5	sing
6.5	31	5.5	katla
8.2	27	8.5	prawn
...

Real-Time Pond Water Dataset for Fish Farming.

70%

Training Set

30%

Testing Set

CRISP DM

Cross Industry Process for Data Mining (CRISP-DM) one of standardize methodology in data mining, analytics, and data science applications.

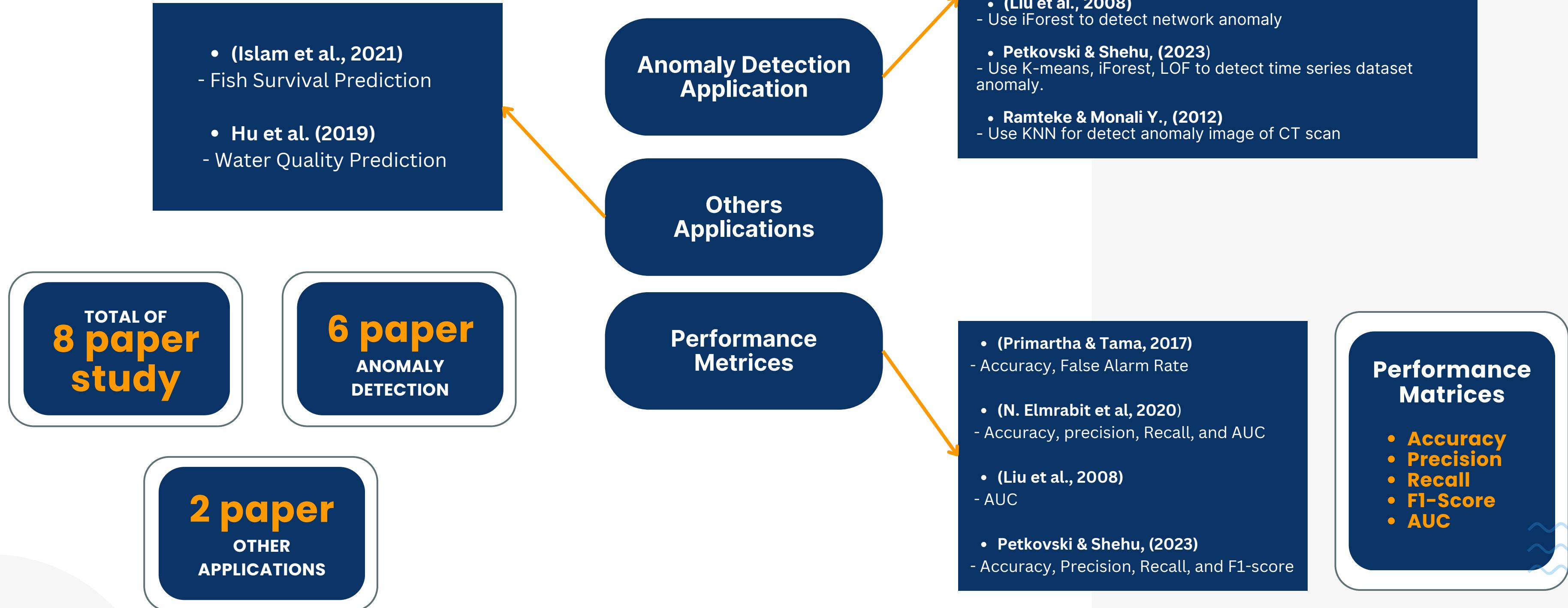
- Business Understanding
- Data Understanding
- Data Preparation
- Modelling
- Evaluation
- Deployment

Proof-of-Concept

This phase involves conducting an analysis on literature and experiment to observe the result

- 01 Planning to develop a machine learning model using CRISP DM
- 02 Use Smart Aquaculture acquired to test the model
- 03 Analyze and evaluate the model after testing phase

OVERVIEW OF STUDIES ON MACHINE LEARNING ALGORITHM IN SMART FARMING



Analysis

01

Identify number of algorithms reviewed about application of machine learning

LSTM	proposed in (Catalano et al., 2022), Hu et al. (2019), (N. Elmrbbit et al, 2020)
RF	proposed in (Primartha & Tama, 2017) , (Islam et al., 2021) , (N. Elmrbbit et al, 2020)
IF	proposed in (Liu et al., 2008) , Petkovski & Shehu, (2023)
KNN	proposed in (Ramteke & Monali Y, 2012), (N. Elmrbbit et al, 2020)
K-means & LOF	proposed in Petkovski & Shehu, (2023)
Others	proposed in (N. Elmrbbit et al, 2020)

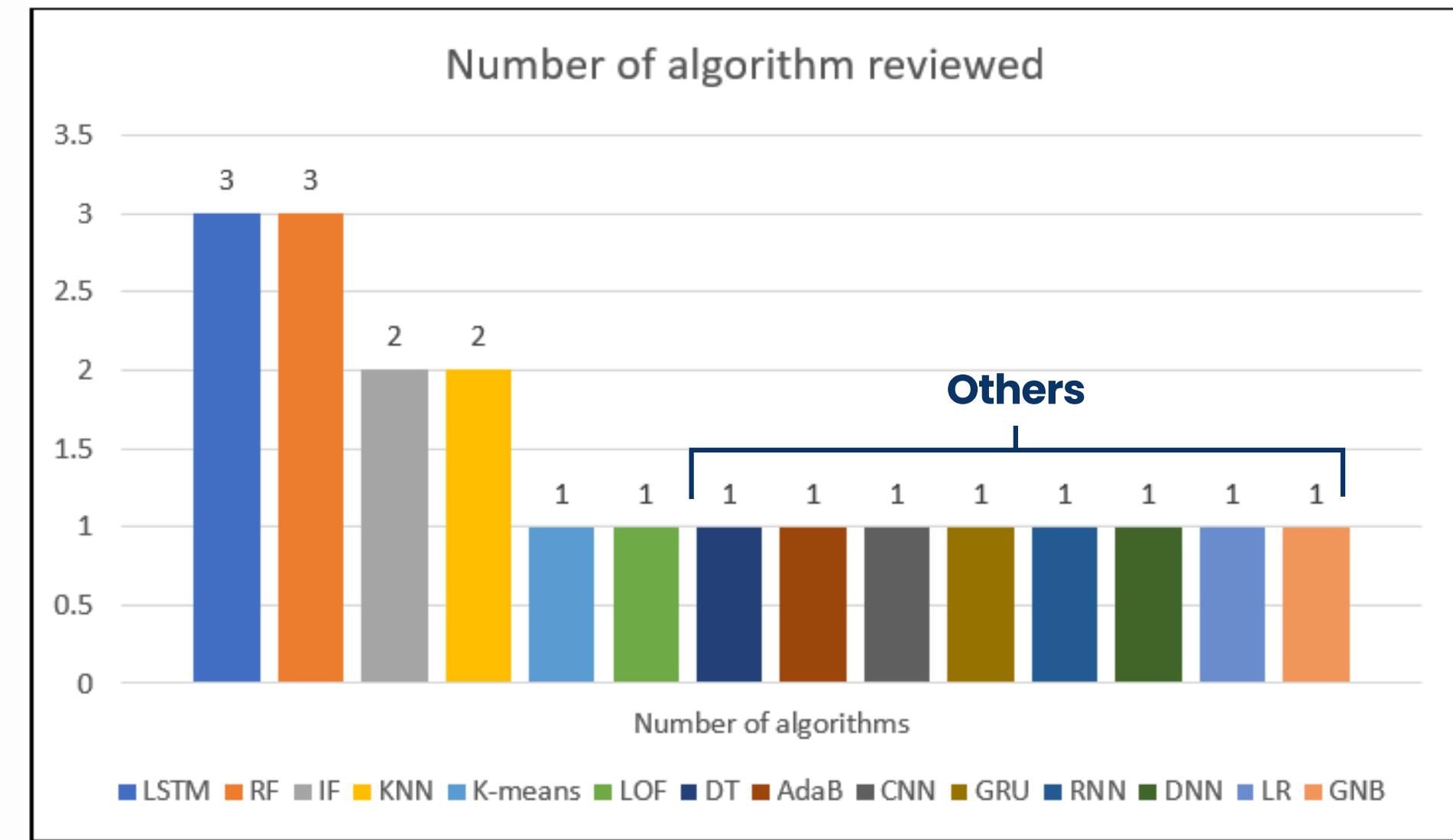


Figure 4. 2: Number of algorithms reviewed

Analysis

02

Identify number of algorithms reviewed that related with anomaly detection application

LSTM	proposed in (Catalano et al., 2022), (N. Elmrbbit et al, 2020)
RF	proposed in (Primartha & Tama, 2017) , (N. Elmrbbit et al, 2020)
IF	proposed in (Liu et al., 2008) , Petkovski & Shehu, (2023)
KNN	proposed in (Ramteke & Monali Y, 2012), (N. Elmrbbit et al, 2020)
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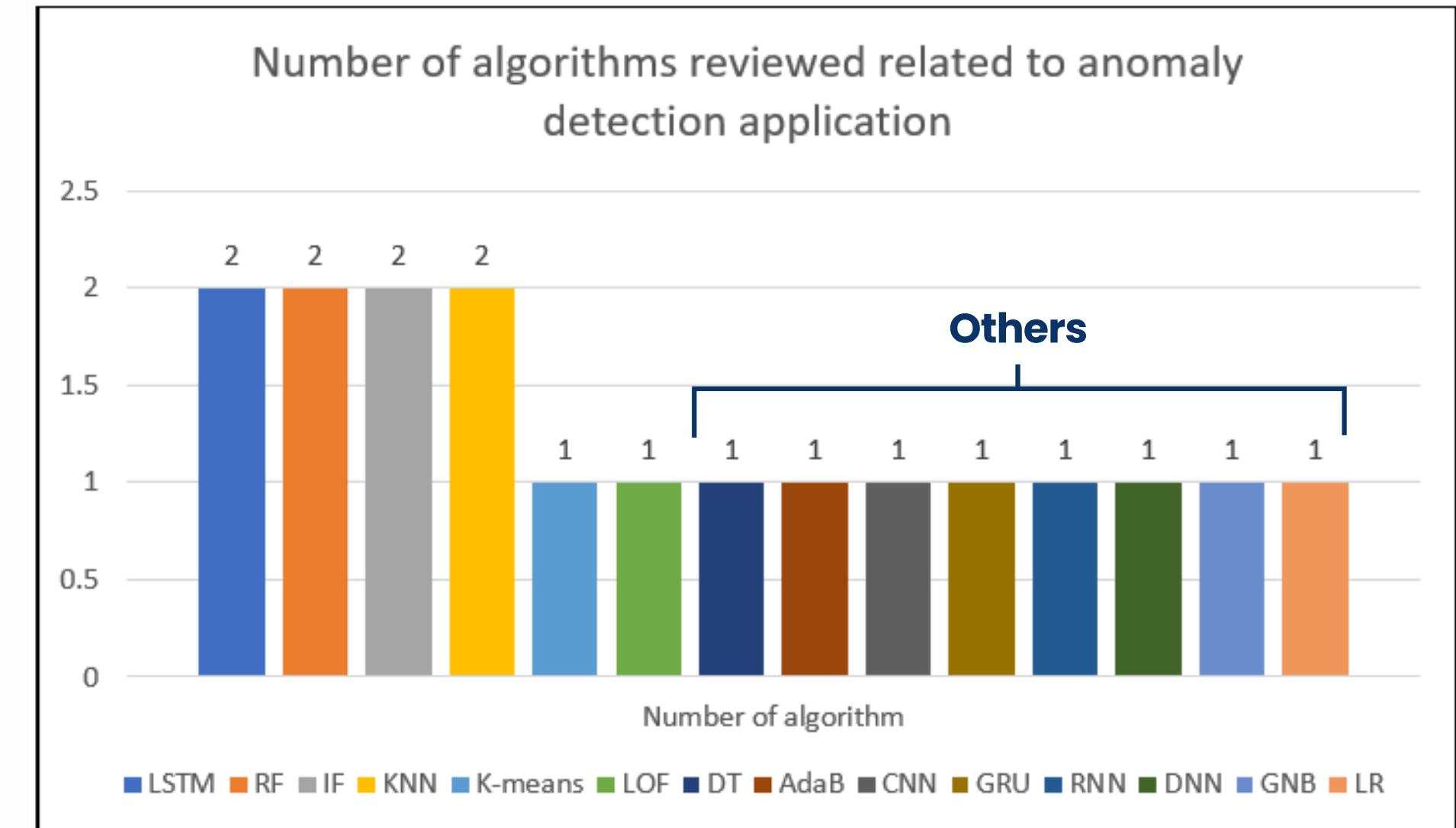


Figure 4. 3: Number of papers reviewed (in context of Anomaly Detection)

Comparison of Machine Learning

Table 2. 3: Comparison of Selected Machine Learning Algorithms

Attributes	LSTM	RF	IF	KNN
Accuracy	High for sequential data	High for structured data	High for anomaly detection	Varies, can be high with proper feature selection
Computational Cost	High due to complex neural network architecture	Moderate; depends on the number of trees	Low due to linear time complexity	Low during prediction, high during training
Speed	Slow due to intensive computation	Moderate; faster than LSTM but slower than Isolation Forest	Fast, especially efficient for large datasets	Slow for large dataset due to distance calculations
Advantages	Excellent for time-series and sequential data	Handles large datasets well; robust to overfitting	Efficient with low memory requirement; scalable	Simple to implement
Disadvantages	Requires large datasets and significant computational resources	Can be memory-intensive, less effective with noisy data	May not perform well on very small datasets; not suited for all types of data	Computationally intensive for large datasets
Robustness	Robust to varying time lags in data	Robust to overfitting and noisy data	Robust to irrelevant attributes and high-dimensional data	Moderate, sensitive to noise and irrelevant features.

Analysis

03

Compare the selected algorithm characteristics from Literature Review

LSTM

High Computational Cost
Low on Speed

RF

High Accuracy, Moderate on
Computational Cost & Speed

IF

Low Computational Cost
High Accuracy & Speed

KNN

Low Computational Cost,
Speed, and Robustness

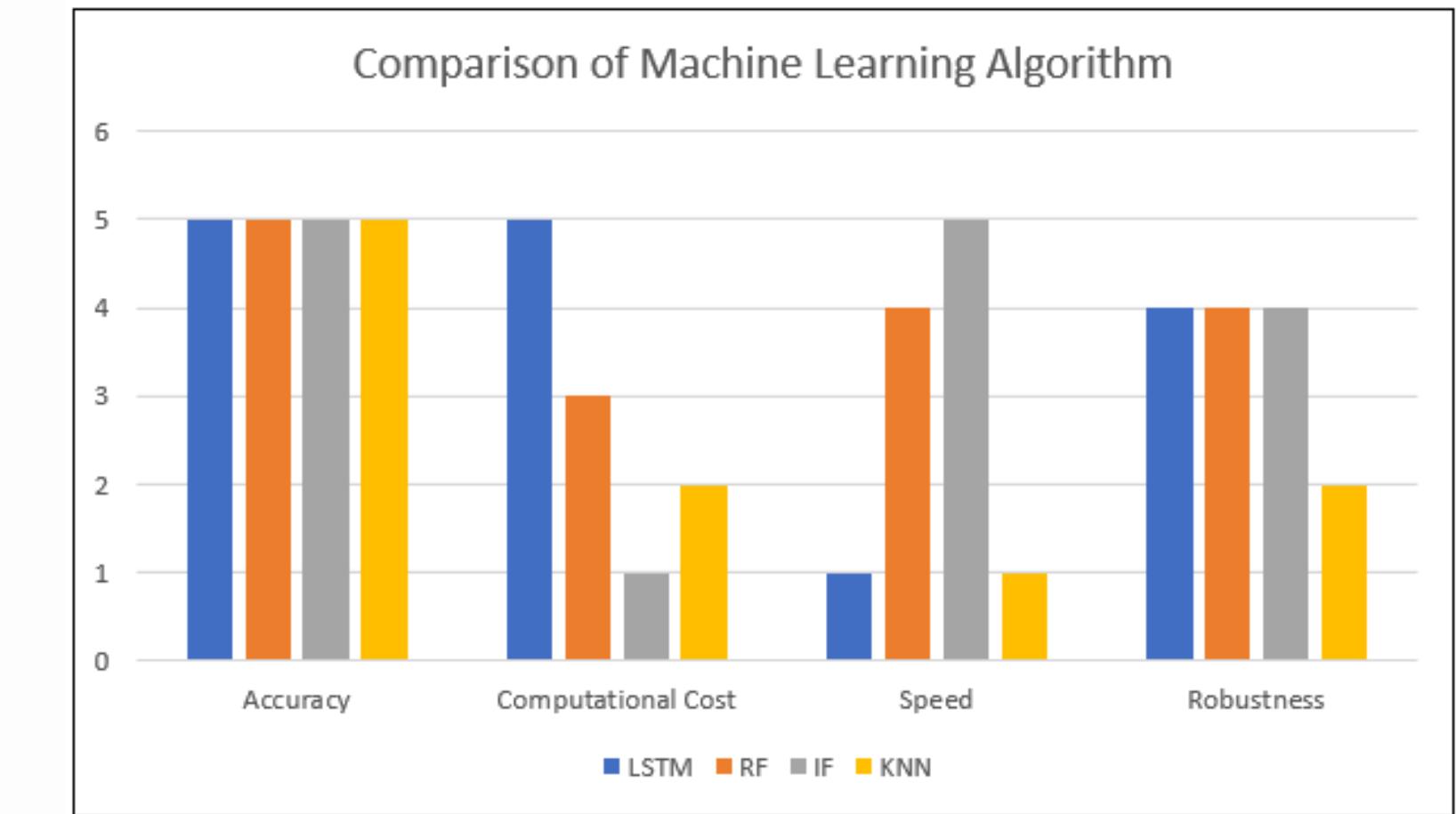


Figure 4. 4: Bar graph of algorithms analysis

Analysis Conclusion

- LSTM is high on computational cost, low speed and not suitable for this smart aquaculture dataset.
- RF, IF, KNN suitable for classifications. Continue the comparative analysis with the dataset and proof-of-concept.

01

Machine Learning Design

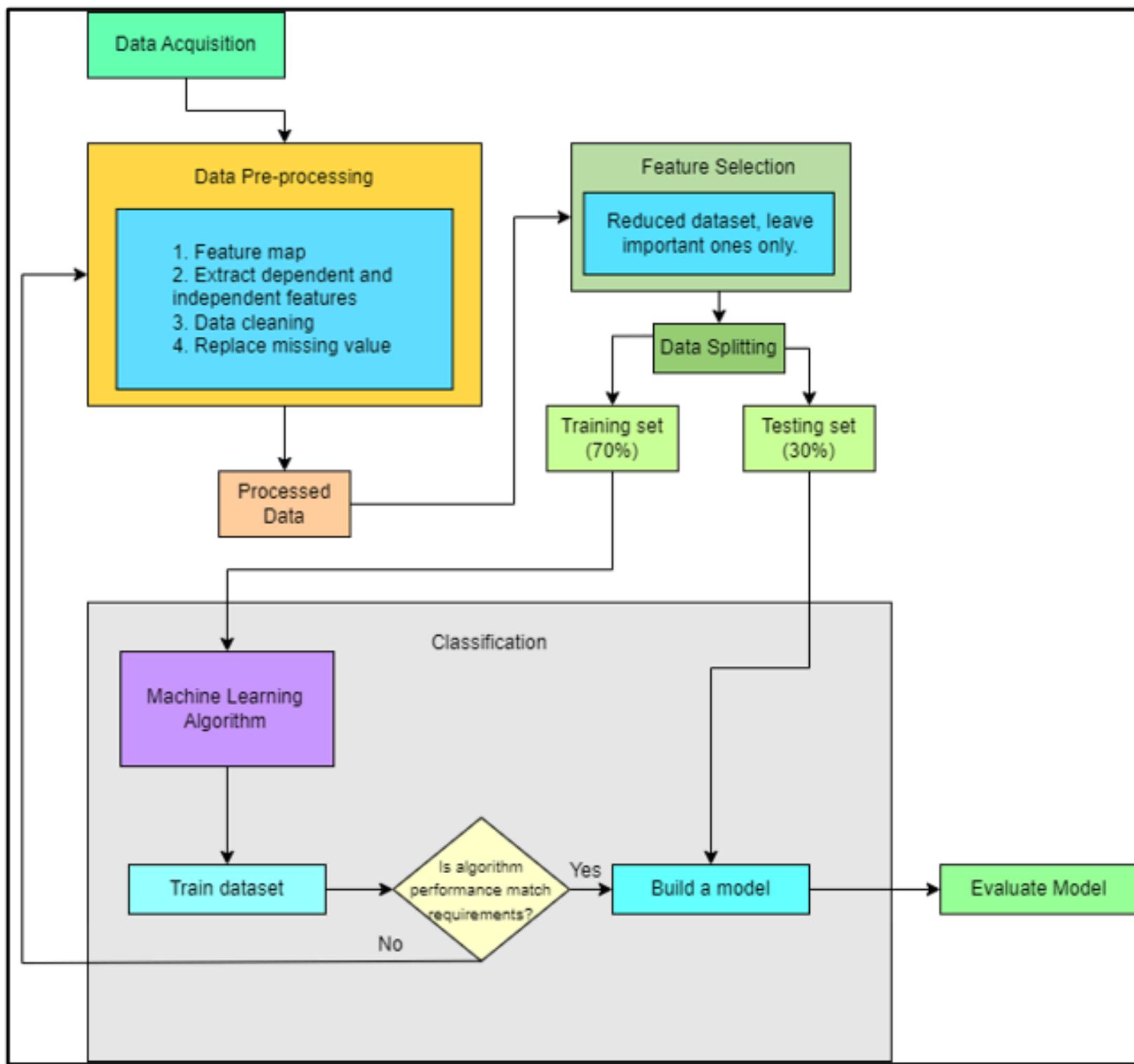


Figure 4. 5: Proposed machine learning flowchart

Design for Proof-of-Concept

- Machine Learning Design
- Anomaly Detection Design
- Data Visualization Design
- Dataset Design

01 Anomaly Detection Design

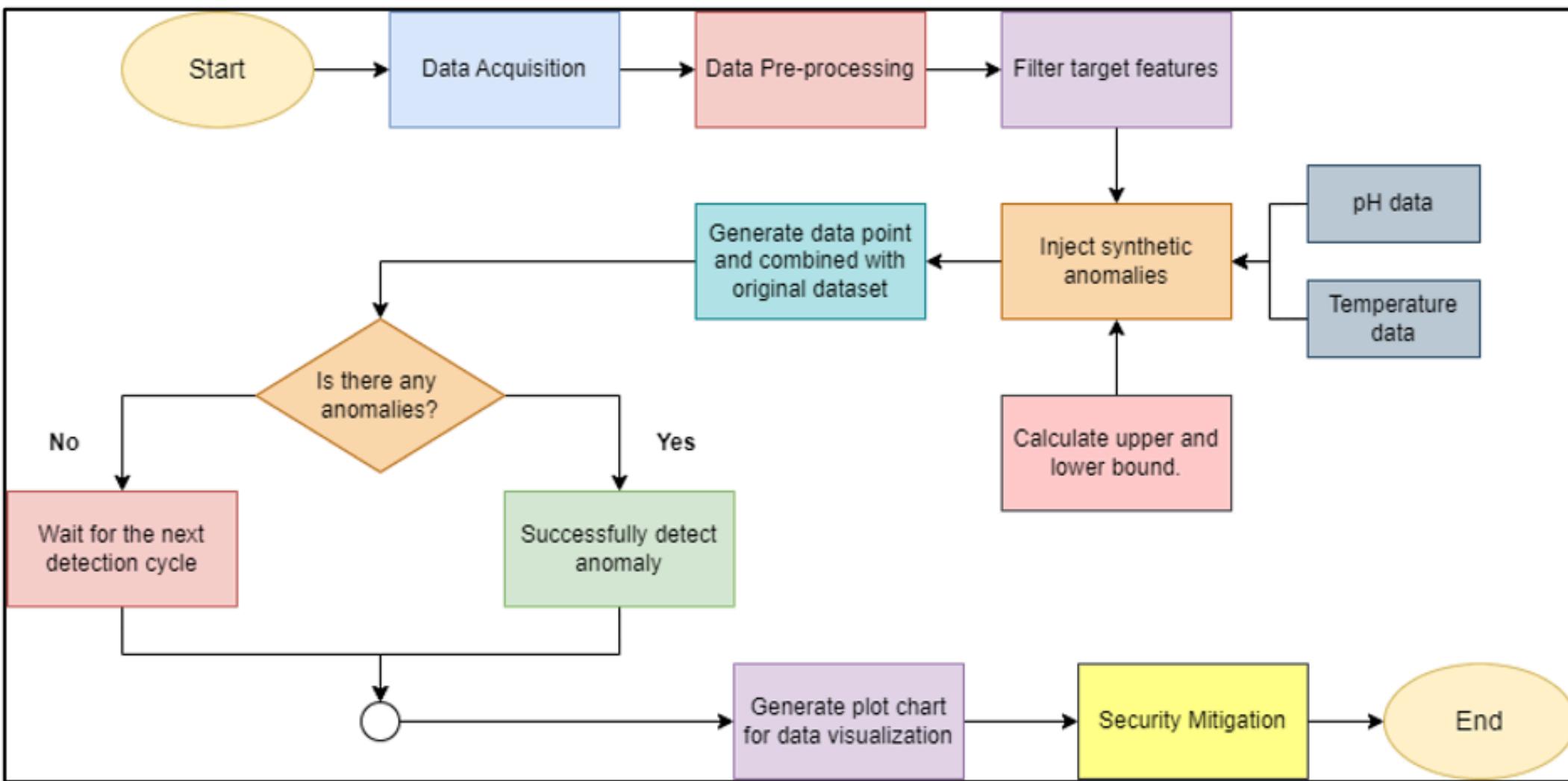


Figure 4. 6: Proposed anomaly detection flowchart

Design for Proof-of-Concept

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01

Data Visualization Design

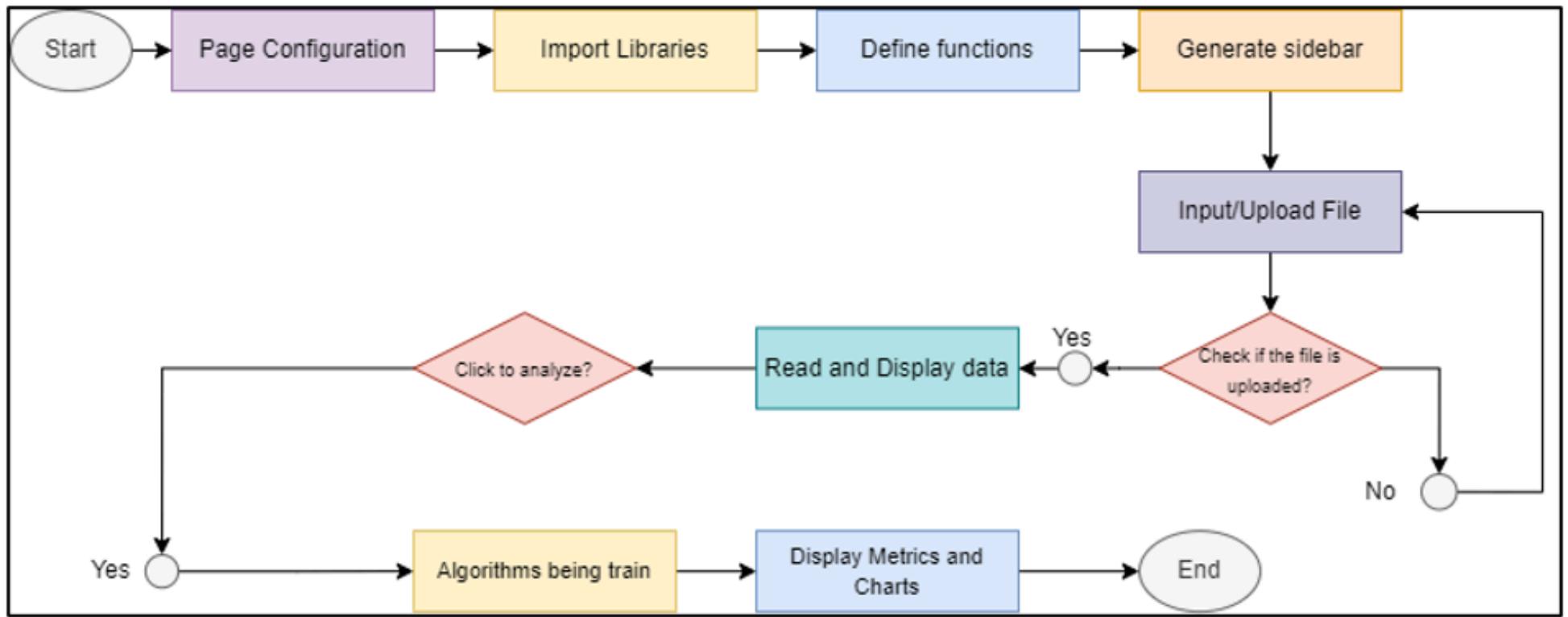


Figure 4. 9: Diagram of Data Visualization Process flowchart

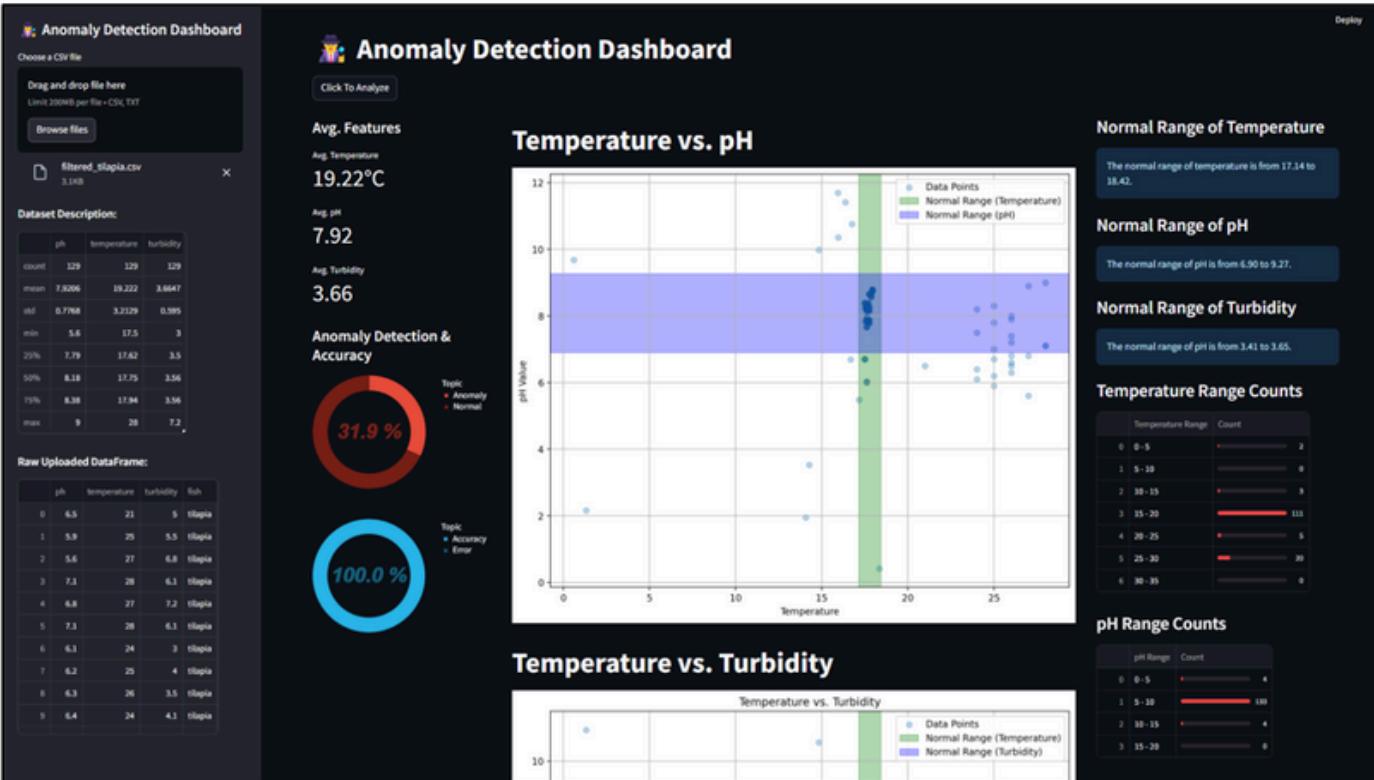


Figure 4. 10: Anomaly Detection Dashboard

Design for Proof-of-Concept

- Machine Learning Design
- Anomaly Detection Design
- Data Visualization Design
- Dataset Design

01

Dataset Design

Table 4. 5: realfishdataset.csv (Real-Time Pond Water Dataset for Fish Farming, 2021)

01

pH	Temperature	Turbidity	Fish
6	27	4	katla
7.6	28	5.9	sing
7.8	27	5.5	sing
6.5	31	5.5	katla
8.2	27	8.5	prawn
...

02

TABLE 4. 6: Result after filter and injecting synthetic anomalies for Tilapia species

pH	temperature	turbidity	status
7.4	26	3	anomaly
8.9	27	3	anomaly
9	28	3.3	anomaly
7.67	17.62	3.56	normal
...

Table 4. 7: Final design of dataset

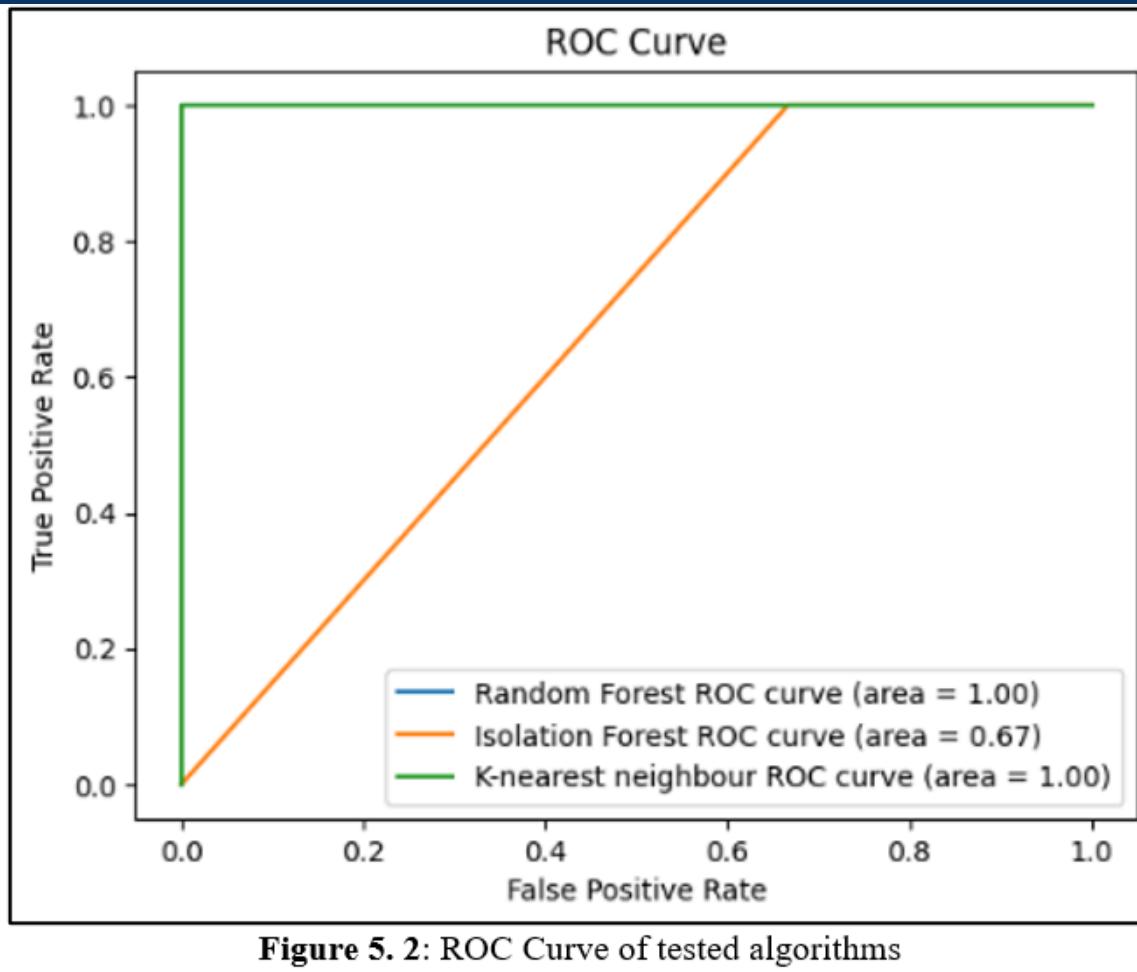
03

ph	temperature	turbidity	status
7.4	26	3	0
8.9	27	3	0
9	28	3.3	0
7.67	17.62	3.56	1
...

Design for Proof-of-Concept

- Machine Learning Design
- Anomaly Detection Design
- Data Visualization Design
- Dataset Design

Analysis



- 01 ROC Curve visualization
- 02 Classification Report

- RF and KNN give the same result, which indicates the algorithms classify the anomaly perfectly.
 - KNN got more disadvantages than RF, therefore RF will be selected.

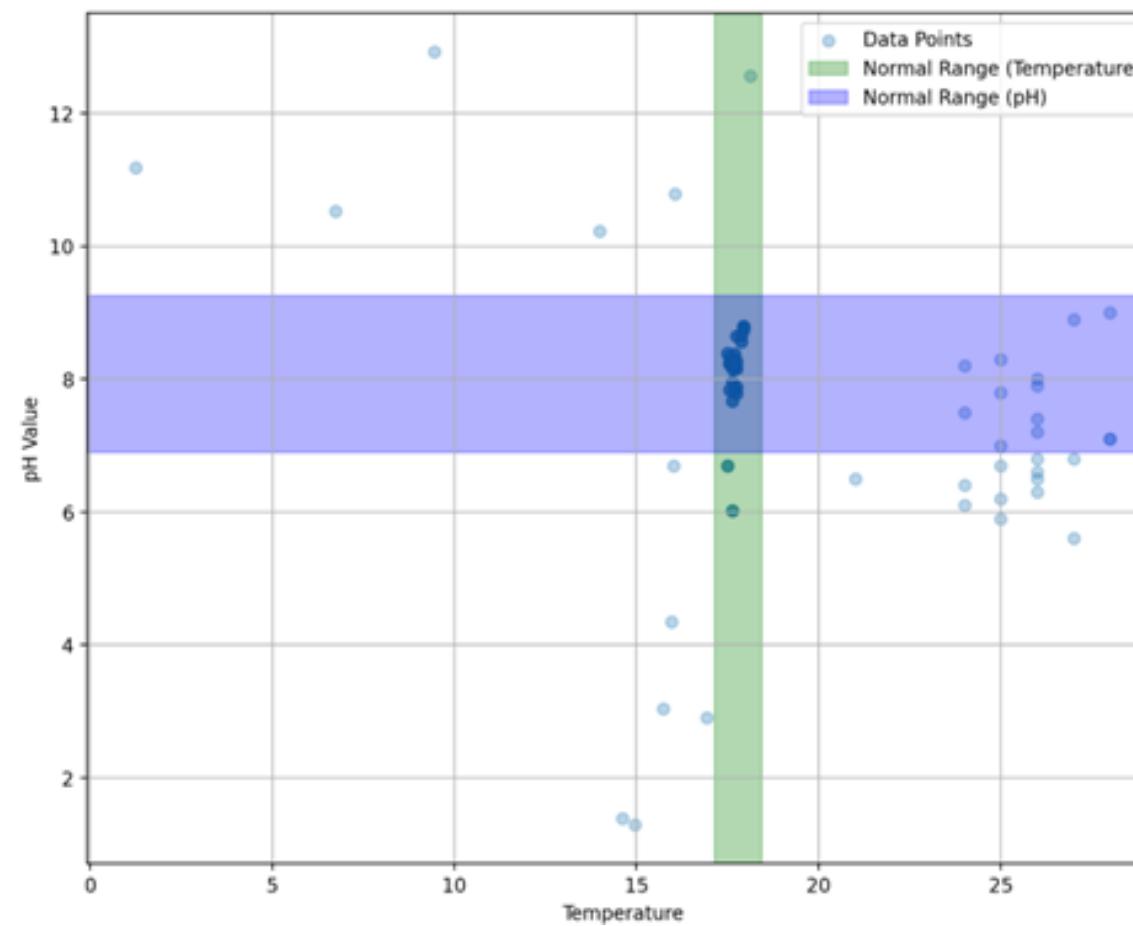
Table 5. 3: Evaluation of tested algorithms.

Anomaly Detection Dashboard Demo

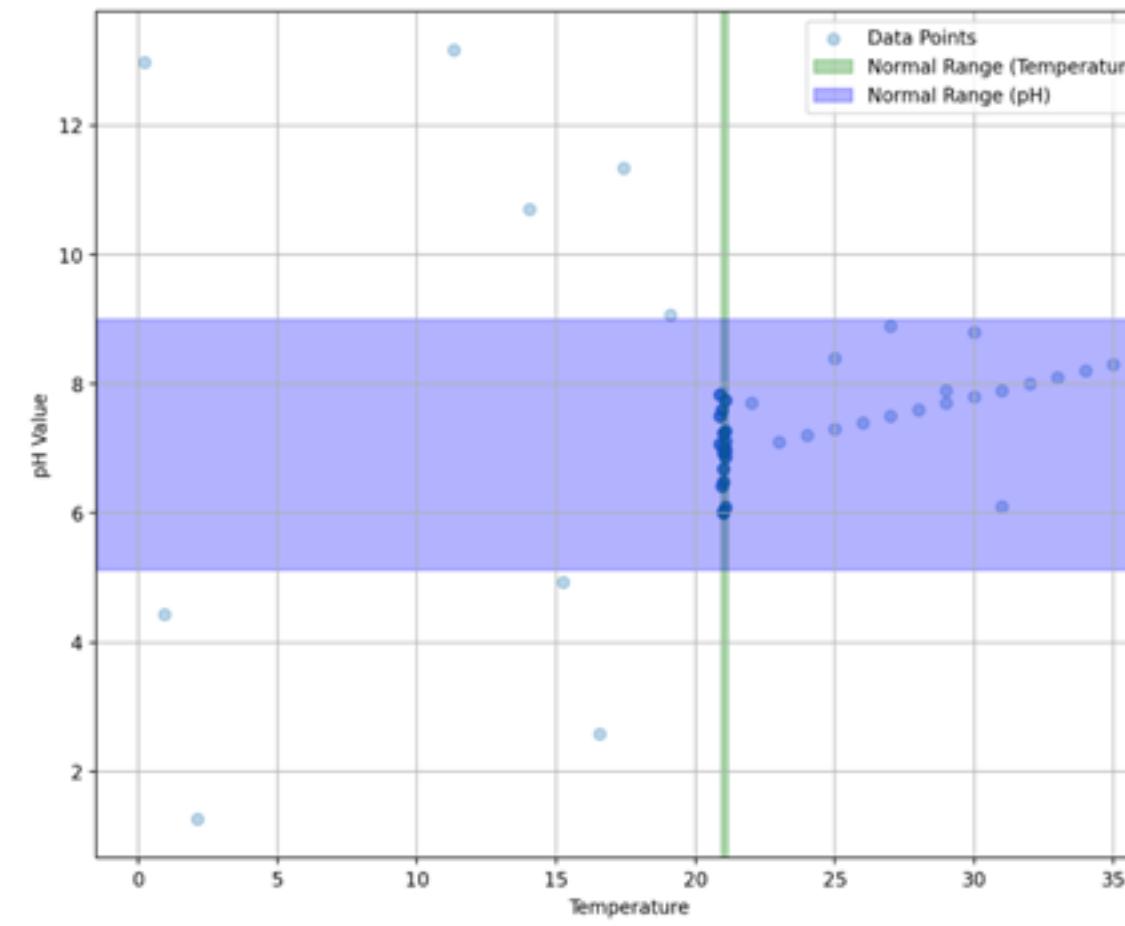
Data analysis and visualization

For analysis, 3 fish species dataset has been extracted from the collected dataset and injected with synthetic anomaly. The species is Tilapia, Rui, and Pangas. Feature to be observe is pH, Temperature and Turbidity

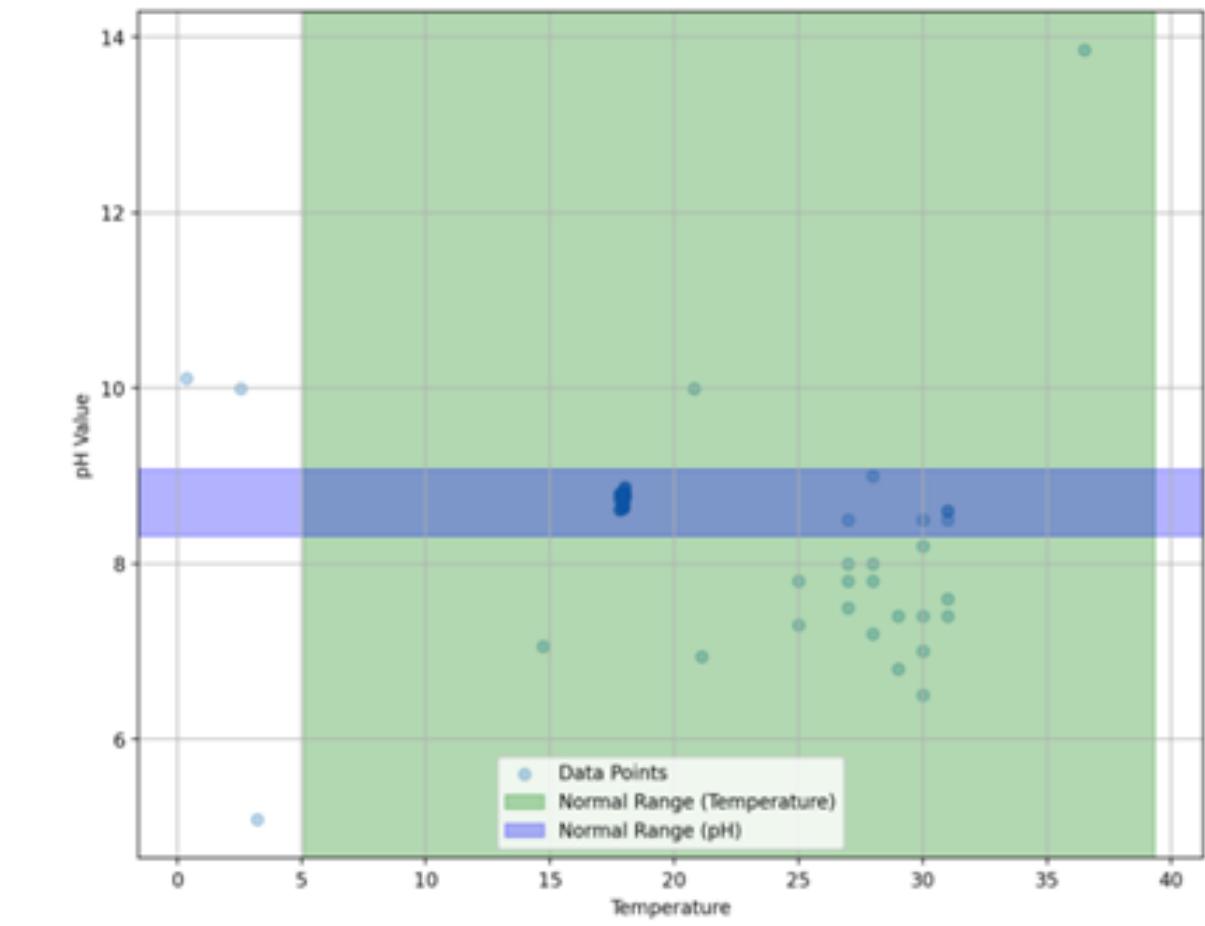
Temperature vs pH Values



Tilapia



Rui

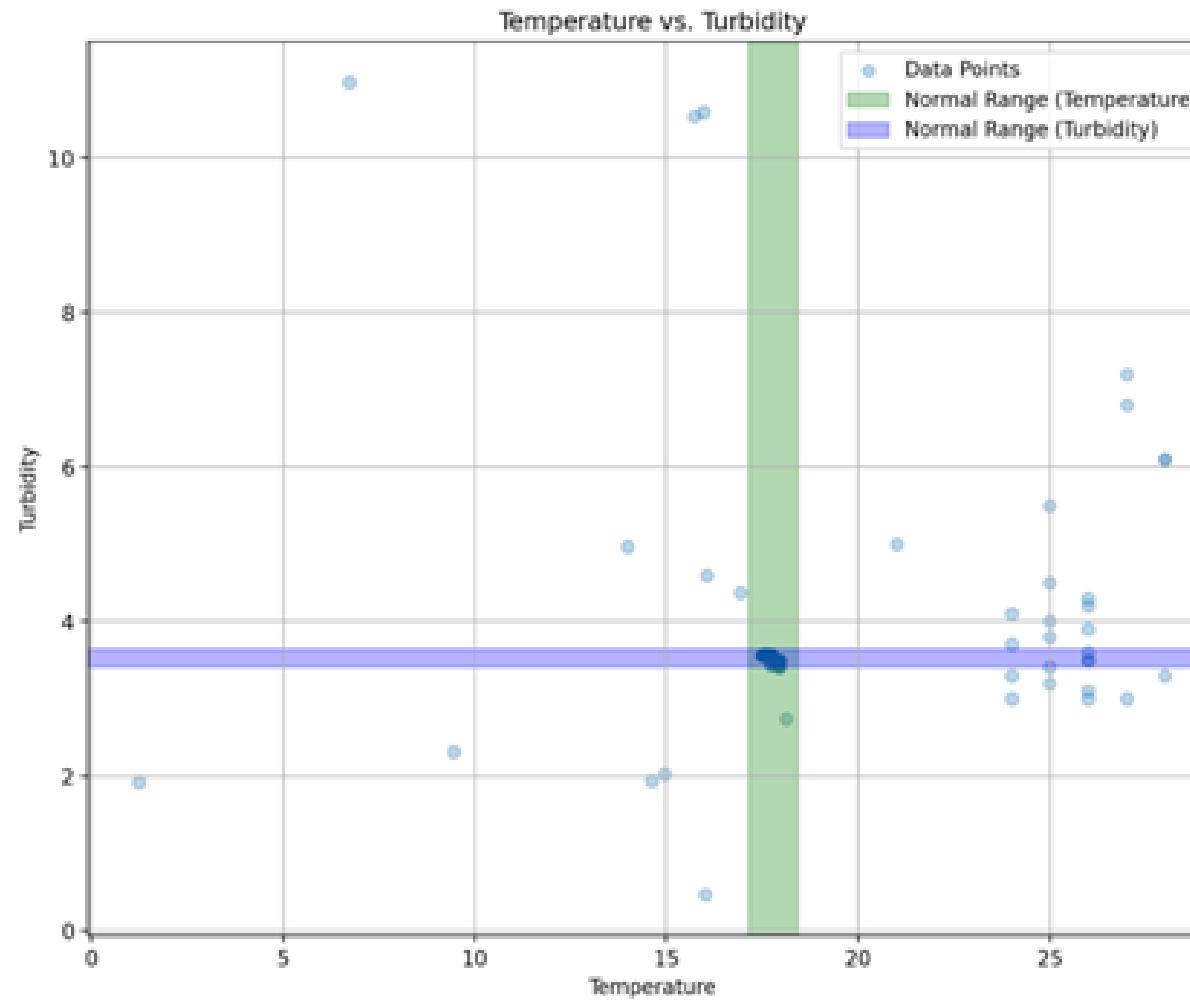


Pangas

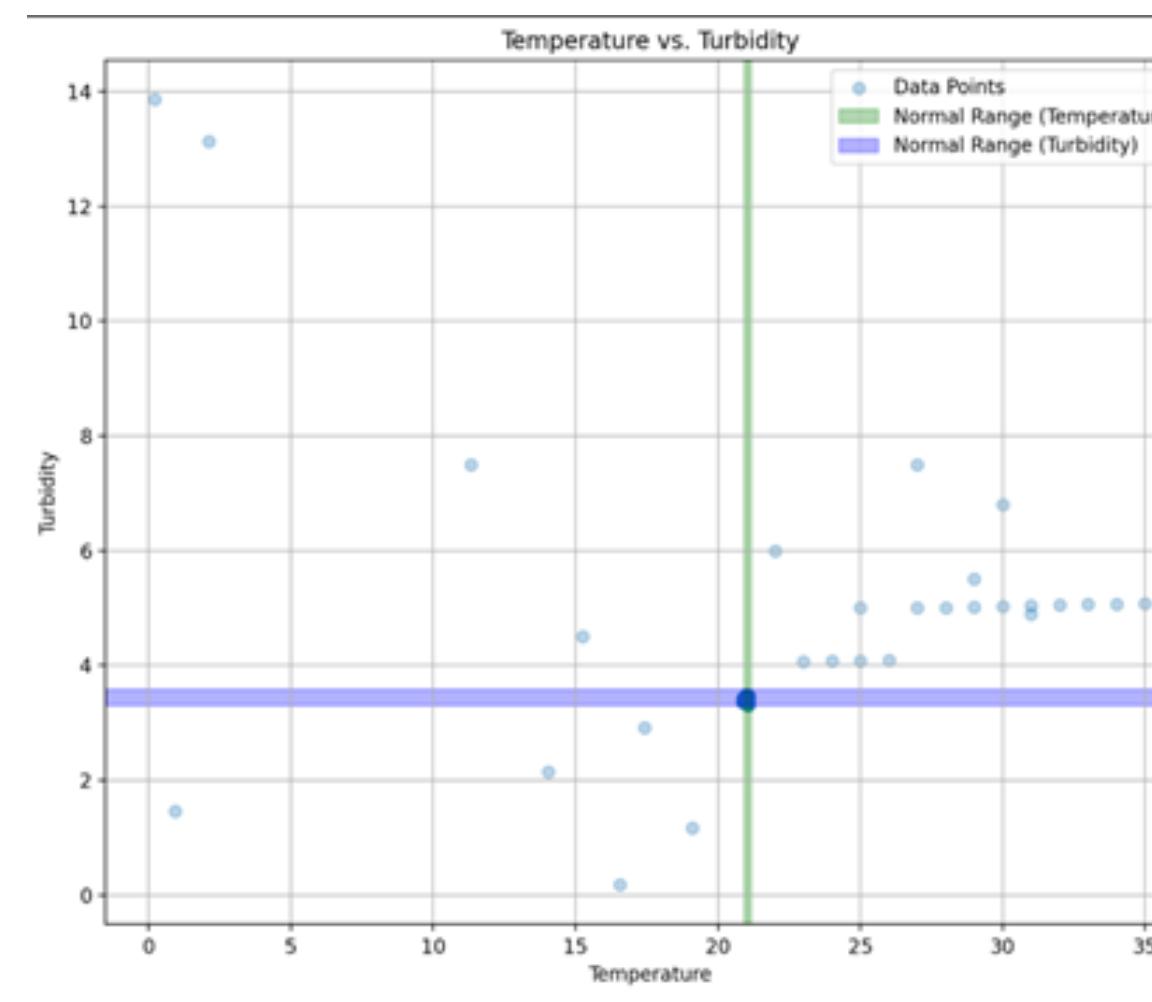
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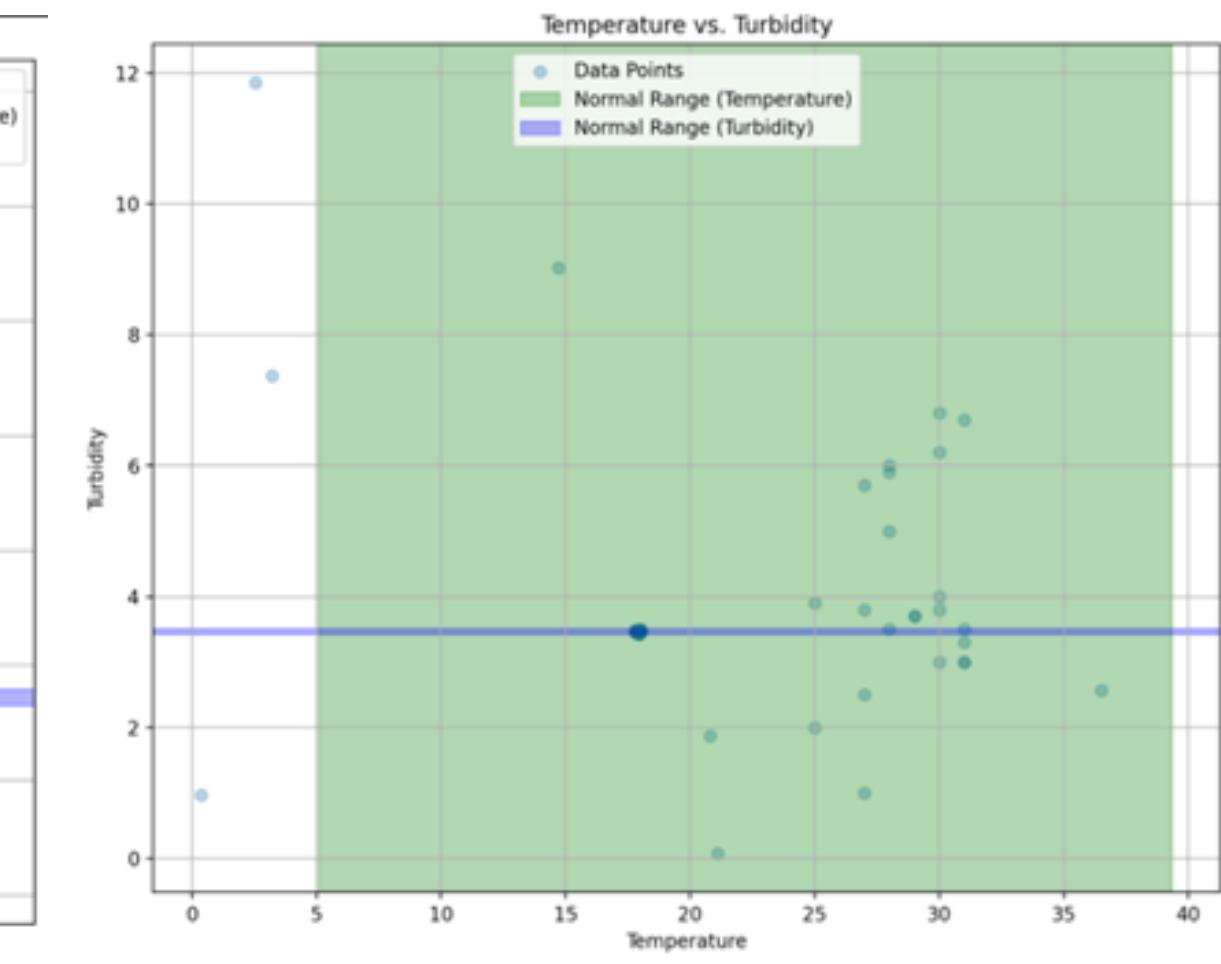
Temperature vs Turbidity



Tilapia



Rui

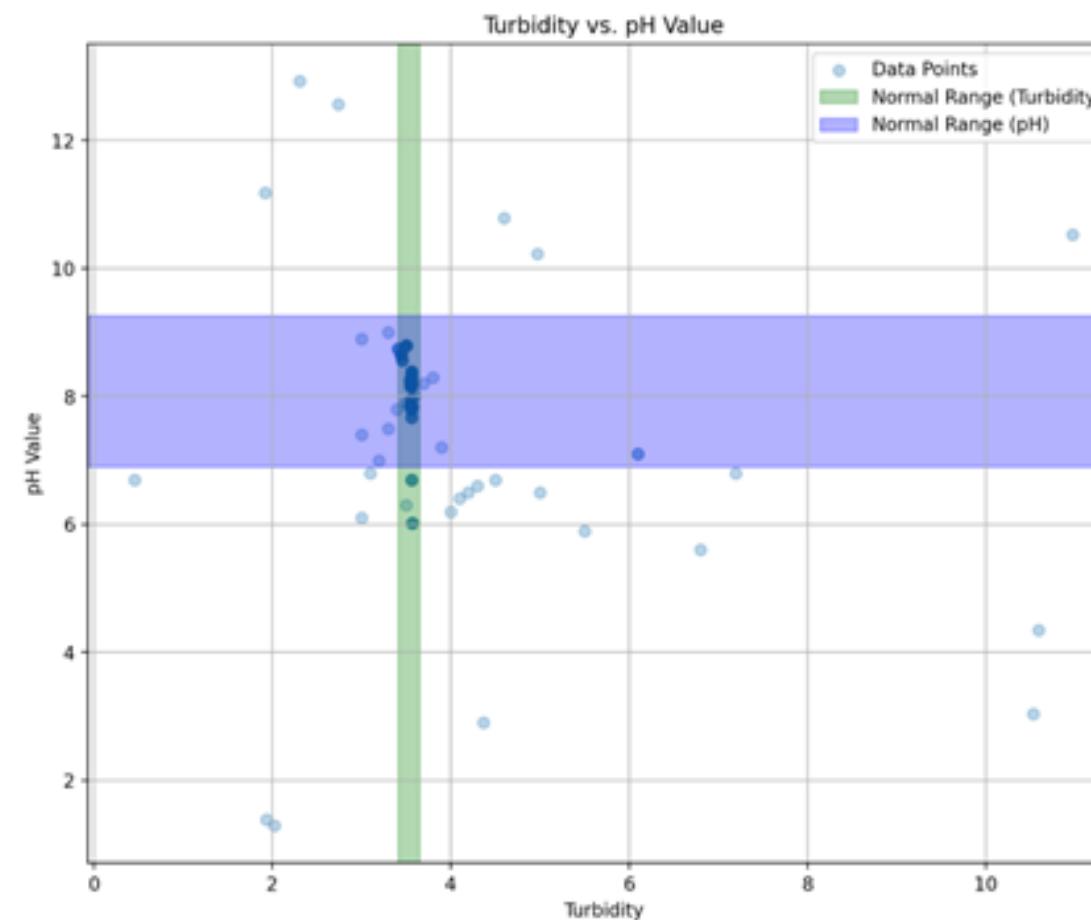


Pangas

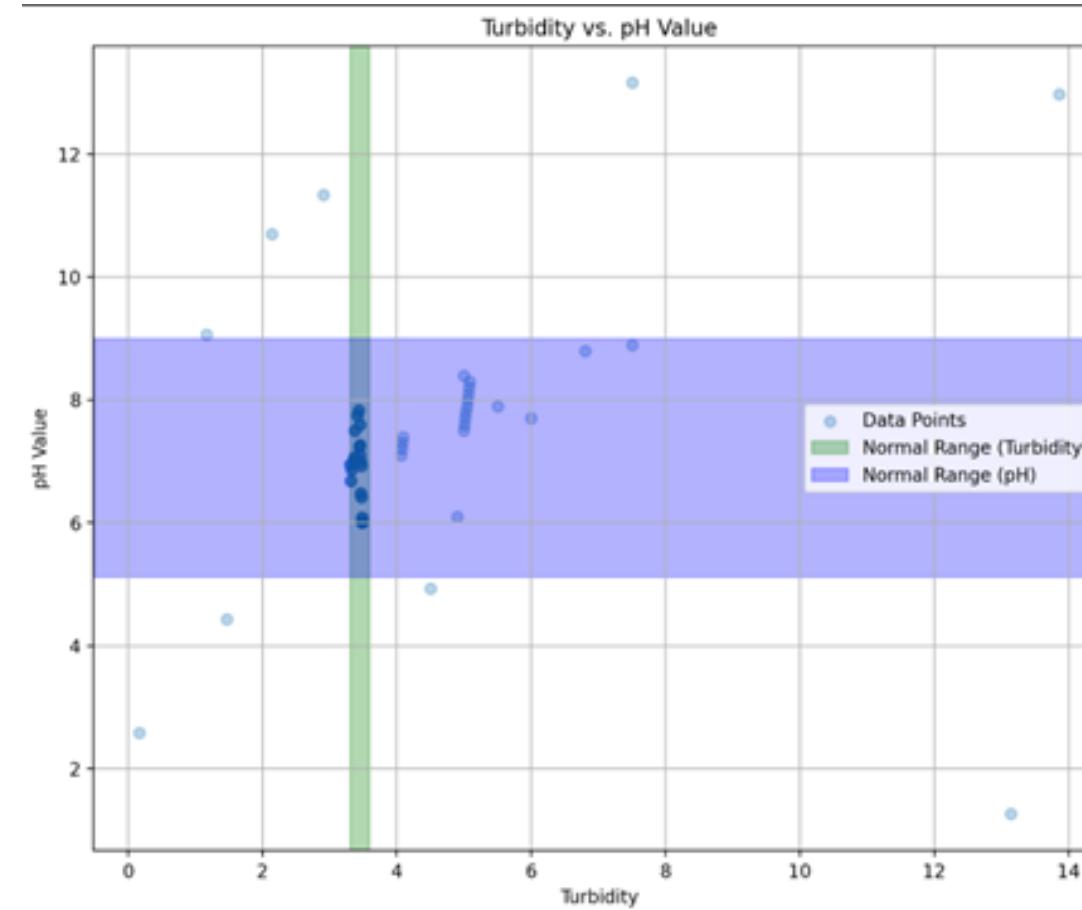
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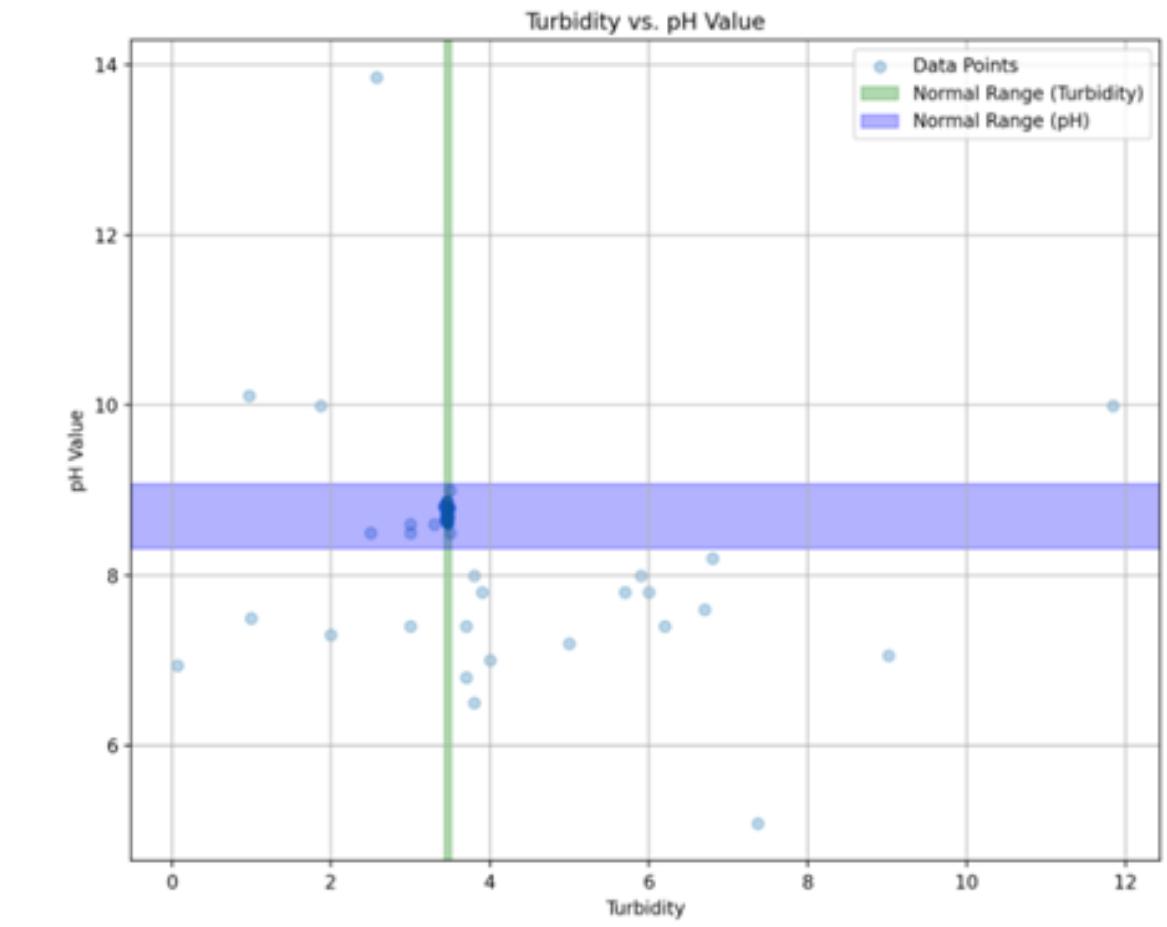
Temperature vs pH Values



Tilapia



Rui



Pangas

Risk Mitigation via Anomaly Detection in Smart Farming environment

A next plan after anomalies has been detection is by conducting a risk mitigation plan. There a several risk mitigation plan can be performed.

Incident Response and Recovery



Endpoint Security



Access Control and Authentication



CONCLUSION

1

Suitable machine learning algorithm for anomaly detection

- Random Forest give the best result compared to other algorithms.
- Achieve high accuracy, precision, recall, f1-score, and ROC-AUC for smart aquaculture dataset.

2

Enhancement for IoT security risk mitigation

- Goals to make smart aquaculture become more secure from possible threats

CHALLENGE & FUTURE WORK

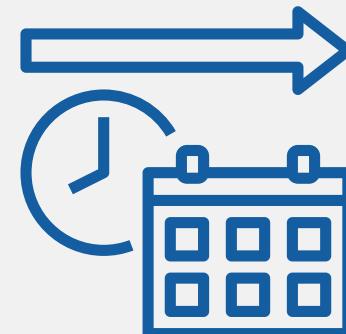


01

Understanding the fundamental of machine learning

02

Learn new framework such as Streamlit, but still can successfully develop a complete program



01

Real-time Anomaly Detection

- Using real sensors and monitor the data
- Set up a small environment, and perform real mitigation plan

02

Enhanced data collection and integration

- Additional environmental factors such as light intensity, CO2 levels
- Integrate with weather forecast to improve anomaly detection

CONCLUSION

Objective	Description	Slides
Objective 1	Review suitable machine learning algorithms for anomaly detection in smart farming	<u>Slide 10: Review Machine Learning Algorithm Application</u> <u>Slide 14: Overview of studies on machine learning algorithm in smart farming</u>
Objective 2	Conduct comparative analysis of machine learning algorithms	<u>Slide 17: Comparison of Machine Learning</u> <u>Slide 15, 16, 18: Analysis of studies and characteristic comparison</u>
Objective 3	Analyze result from the selected machine learning model	<u>Slide 25, 26, 27: Data analysis and visualization</u>

ANOMALY DETECTION FOR SMART FARMING VIA
MACHINE LEARNING

Q&A SESSION

FINAL YEAR PROJECT 23 / 24

ANOMALY DETECTION FOR SMART FARMING VIA
MACHINE LEARNING

THANK YOU!

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