SMART AQUATIC HEALTH MONITORING SYSTEM

Dissolved Oxygen Prediction via DL Model for Aquatic Health

TEAM DATA DYNAMOS - GAT11

C K LEKHANA

M HARSHITHA

NIDHI K N

CHAITANYA A M

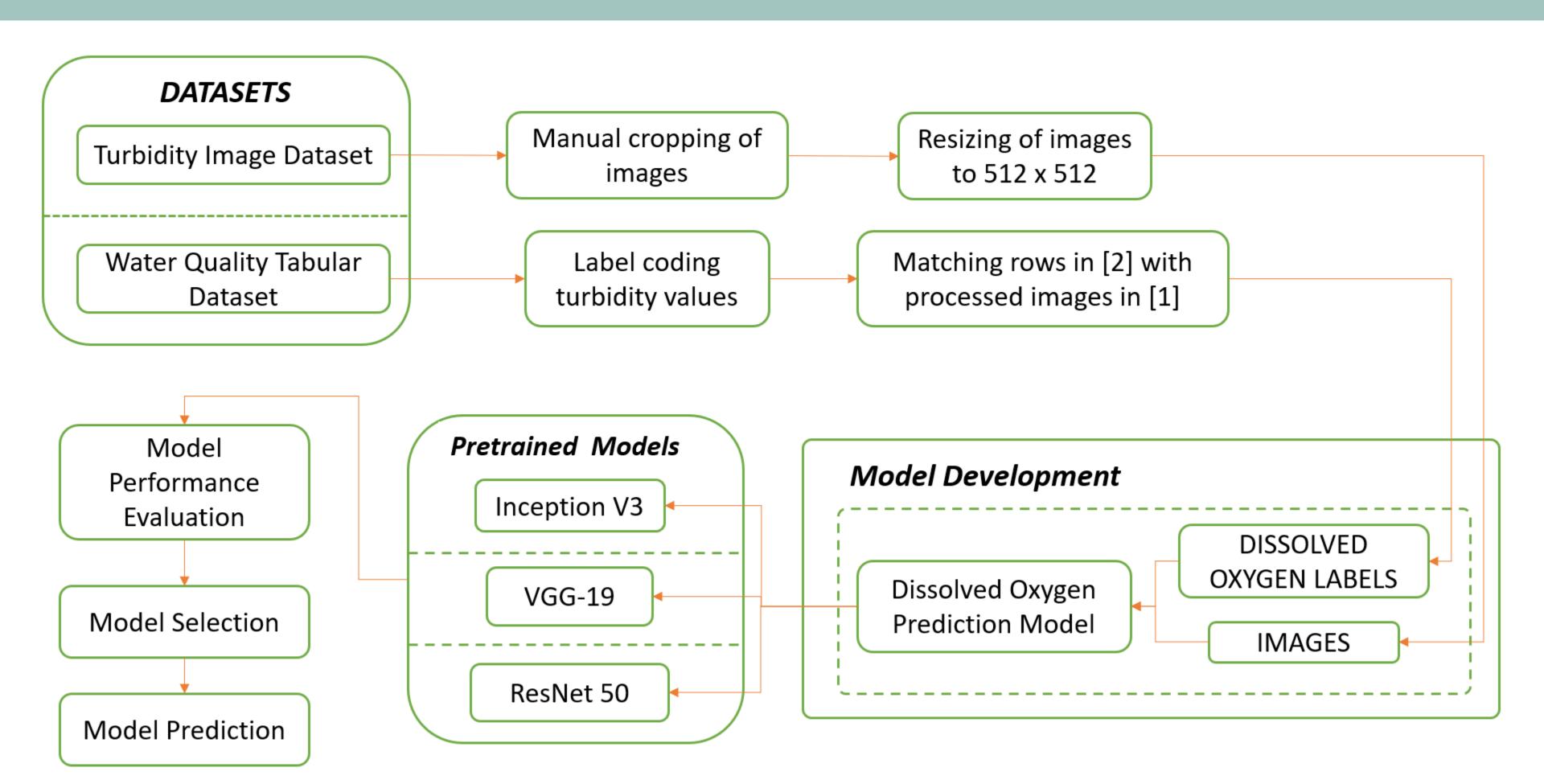
BHAVANA SHREE N

GAGANA D M

PROBLEM STATEMENT

- From aquaculture to sustenance of biodiversity to climate regulations, the Aquatic Ecosystem plays a pivotal role in human survival and prosperity.
- The existing technologies include IoT based Aquaculture health monitoring system [1], Water quality monitoring system [2] among others, most of which use multiple sensors making the monitoring systems bulkier and costlier due to integration of multiple sensors and engines for accurate data sensing.
- It is pertinent to provide quicker, easier solutions that leverage emerging ML/DL techniques to help monitor aquatic ecosystems in real time and mitigate biochemical toxicity hazards along with enabling environmentalists/scientists in developing efficient biosafety measures for aquatic species.

Model Architecture



MODEL RESULTS

MODEL	Epochs	Batch Size	Optimisers	Accuracy	Loss
Inception V3	10	32	Adam	0.4949	1.1256
Inception V3	4	32	Adam(lr=0.002)	0.4735	1.1372
ResNet 50	6	32	Adam	0.3241	1.2906
VGG-19	4	32	Adam	0.0044	3.3871

INCEPTION V3 MODEL 1

```
model.fit(train_dataset, validation_data=val_dataset, epochs=8)
\overline{\mathbf{T}}
    Epoch 1/10
                              - 354s 29s/step - accuracy: 0.3929 - loss: 1.4722 - val accuracy: 0.4224 - val loss: 1.4516
    12/12 ---
     Epoch 2/10
                               365s 28s/step - accuracy: 0.3930 - loss: 1.4660 - val accuracy: 0.4310 - val loss: 1.2849
    12/12 -
     Epoch 3/10
                              - 383s 28s/step - accuracy: 0.3398 - loss: 1.3893 - val accuracy: 0.5000 - val loss: 1.1065
    12/12 —
     Epoch 4/10
                              - 334s 28s/step - accuracy: 0.4207 - loss: 1.1787 - val accuracy: 0.4741 - val loss: 1.2230
    12/12 -
     Epoch 5/10
                              - 376s 28s/step - accuracy: 0.4976 - loss: 1.1209 - val accuracy: 0.3966 - val loss: 1.1748
    12/12 ---
    Epoch 6/10
                              - 381s 28s/step - accuracy: 0.4416 - loss: 1.1989 - val accuracy: 0.4310 - val loss: 1.1833
    12/12 ----
     Epoch 7/10
                              - 335s 28s/step - accuracy: 0.4610 - loss: 1.1915 - val accuracy: 0.4224 - val loss: 1.1810
    12/12 -
     Epoch 8/10
                              - 338s 29s/step - accuracy: 0.5147 - loss: 1.1044 - val_accuracy: 0.3362 - val loss: 1.2422
    12/12 -
    Epoch 9/10
                              - 373s 28s/step - accuracy: 0.3621 - loss: 1.2295 - val accuracy: 0.5172 - val loss: 1.1158
    12/12 —
    Epoch 10/10
                              - 328s 28s/step - accuracy: 0.4949 - loss: 1.1256 - val accuracy: 0.4483 - val loss: 1.1853
    12/12 —
    <keras.src.callbacks.history.History at 0x7b00ad869630>
```

ResNet - 50 Model

```
model.fit(train_dataset, validation_data=val_dataset, epochs=10)
 Epoch 1/10
                               460s 38s/step - accuracy: 0.3864 - loss: 4.3605 - val accuracy: 0.3362 - val loss: 2.0543
     12/12 -
    Epoch 2/10
    12/12 -
                               440s 37s/step - accuracy: 0.3308 - loss: 2.4900 - val_accuracy: 0.3017 - val_loss: 2.2861
    Epoch 3/10
                               451s 38s/step - accuracy: 0.3063 - loss: 2.2406 - val_accuracy: 0.2672 - val_loss: 1.3876
    12/12 -
    Epoch 4/10
                               452s 38s/step - accuracy: 0.3462 - loss: 1.4433 - val_accuracy: 0.3017 - val_loss: 1.2904
    12/12 -
    Epoch 5/10
                              446s 38s/step - accuracy: 0.3087 - loss: 1.4803 - val_accuracy: 0.2759 - val_loss: 1.2836
    12/12 -
    Epoch 6/10
    12/12 -
                              498s 37s/step - accuracy: 0.3241 - loss: 1.2906 - val_accuracy: 0.2586 - val_loss: 1.2747
```

FUTUTRE SCOPE

Currently, the proposed prototype predicts aquatic health status only when the user inputs an underwater image and other required sensor data. This prototype can be further scaled by:

- 1) automation of sensor data and image input to the prediction model.
- 2) explore complex aquatic systems that affect aquatic health and try capture those complex systems in an image/video for more accurate prediction.

WOW FACTOR!

One-Click Solution for Predicting Aquatic Ecosystem Health. Our proposed model enables users to instantly predict the health status of an aquatic ecosystem by simply uploading an image as input.

This work also falls under the following Sustainable Development Goals:

- 1) Goal 6: Clean water and Sanitation
 The model can be used to predict water potability
- 2) Goal 14: Life Below Water

By predicting the ecosystem's health status, appropriate measures to overcome major issues like ocean warming, ocean acidification and coastal acidification which can adversely affect the life under water.

ABSTRACT REFERENCES

[1] Demetillo, A. T., Japitana, M. V., & Taboada, E. B. (2019). A system for monitoring water quality in a large aquatic area using wireless sensor network technology. Sustainable Environment Research, 29(1), 1-9.

[2] Sarwar, A., & Iqbal, M. T. (2022). IoT-Based Real-Time Aquaculture Health Monitoring System. European Journal of Electrical Engineering and Computer Science, 6(4), 44-50.

DATASET REFERENCES

IMAGE DATASET:

Trejo-Zúñiga, I., Moreno, M., Santana-Cruz, R. F., & Meléndez-Vázquez, F. (2024). Deep Learning-Driven of Turbidity Levels Dataset (Version 1.0) [Data set]. Zenodo.

TABULAR WATER QUALITY DATASET

https://www.kaggle.com/datasets/shreyanshverma27/water-quality-testing

THANK YOU!

DATA DYNAMOS - GAT11