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A CNN Model for Determining the Land Acquisition in Chennai Puzhal Lake Using Edge Impulse and Justifying the Anomaly with Computer Vision

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***Abstract* - Artificial intelligence has had a significant impact on all sustainable development goals. Disaster management is one of the most pressing challenges of this day, as highlighted in Sustainable Development Goals 13 and 15. And this technology, artificial intelligence, has a stronger impact on proper urban planning and disaster management. Disasters are divided into two types: natural and man-made. Natural disasters are uncontrollable, whereas man-made disasters can be expected and managed. Though there are numerous reasons for man-made catastrophes, increased urbanization and land purchase to conceal urban water bodies are solid root causes of disasters such as floods in metropolitan areas. AI has a crucial role in estimating the annual rate of increase in land acquisition. Considering the new era of technology, using the Bhuvan 2.0 software, the satellite image (considering the satellite map) of Puzhal Lake is obtained from the Bhuvan 2.0 website for the years 2015, 2017, and 2021. In this paper, an attempt is made to use a computer neural network with these images in Edge Impulse software to determine the occurrence of land acquisition around Puzhal Lake, as well as to determine the anomaly by comparing satellite images of the lake taken in 2015 and 2021 using computer vision.**

***Keywords:* Buvan 2.0, Anomaly Detection, Edge Impulse Software, Ishikawa Analysis**

I. Introduction

Land acquisition has become a major issue in society, particularly in metropolitan areas. Because of the increase in population, floods are becoming more common in every part of the planet. Though pollution contributes significantly to climate change, man-made disasters such as land acquisition continue to be causes of these disasters Kushwaha et al., 2025. Chennai, the capital city of Tamil Nadu in India, has lately seen severe disasters in the years 2015, 2021, 2022 and 2023. So far, much has been said about the lack of efficient rainfall drainage systems, but there is another painful truth: most of Chennai's lakes are occupied by the arbitrary construction of residential and commercial buildings in those locations. As a result, the lakes are vanishing year after year, resulting in the man-made disaster known as Floods during heavy rainy seasons. Fig 1 depicts the Ishikawa reasons for the Chennai floods during the wet season.

In this article, land acquisition surrounding Chennai's Puzhal lake is studied, and it is analysed using both a computer vision algorithm and AI-powered Edge Impulse software. This type of study raises the red flag issue in which lakes in major cities are disappearing due to poor urban planning, addressing increasing population expansion

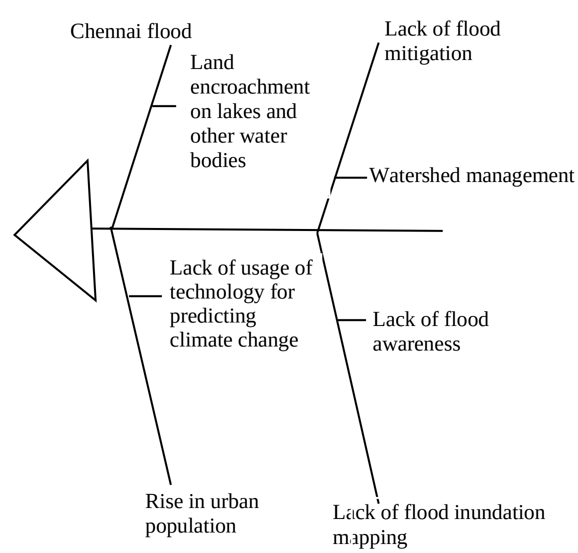

Fig. 1 Ishikawa Analysis of Chennai Flood

II. LITERATURE REVIEW

The literature review is made on two different themes, which includes survey on anomaly detection using satellite images and a survey on computer vision-based edge detection for the given input images. (Zhou & Tang, 2016) proposed using satellite pictures to detect anomalies in a continuous time series using the z-score of season-trend model residuals (ZSTR) (William et al., 2025). Castillo et al. developed an Earth observation-based anomaly detection strategy for increasing agricultural output with limited resources. (Wang et al., 2021) developed an artificial neural network for identifying erroneous satellite images by removing issues such as color cast, missing data, anomalous color, and so on. (Marinho et al., 2023; Frincke & Wang, 2025) suggested the ADS-KT approach for mapping contaminated water basins hidden by clouds in satellite images. (Popescu et al., 2024) suggested a patch detection approach to handle noisy and missing satellite data. (Pinaso et al., 2024) showed how the Edge Impulse program is utilized as a machine learning tool, particularly for image processing. (Nikhitha et al., 2020) used computer vision to identify an anomaly with a change in pixel count in satellite pictures of Puzhal Lake. (Cannas et al., 2024) suggested a convolutional neural network for detecting satellite pictures of SRV using SOTA techniques. (Avolio et al., 2021) discussed dynamic time warping for anomaly detection in satellite pictures, which helps farmers. (Pang et al., 2018) examined prediction interval optimization for anomaly detection in satellite time series. (Rajendran et al., 2024) proposed the use of Edge Impulse software for anomaly detection in industries, with audio signals as input (Frinckc & Wang, 2025; Herrmann et al., 2024) presented deep anomaly detection to address the problem of telemetry data in satellite photos (Wilamowski, 2025; Patel et al., 2016). suggested a solution for overcoming problems in multispectral satellite photos. Li et al. suggested an ASR model for anomaly segmentation with high spatial resolution. (Zhao et al., 2024) investigated reconstruction theory for detecting anomalies in satellite photos. (Ghazal et al., 2024) introduced a computer vision technology to the digital life cycle of crops for precision agriculture. (Fetai et al., 2021) employed a programming-based deep learning technique to predict observable land borders. (Dhanya et al., 2022) suggested a computer vision technique for smart agriculture that improves irrigation management and seed quality evaluation (Noori & Salman, 2024; Khan et al., 2024) suggested a transformer-based model for predicting increased land use and cover. (Sedighkia & Datta, 2023) used two spectral images from Landsat 8 to test and train the machine learning model. (Hao et al., 2024) proposed a method for selecting an effective deep learning model for land use mapping. (Gu & Zeng, 2024) explored the problems and opportunities for detecting land cover change with high-resolution artificial intelligence-based satellite remote sensing. (Li et al., 2009) investigated change detection using SAR pictures and the CBR matching technique. (Sivasubramaniyan & RajaPerumal, 2024) proposed applying a machine learning technique using satellite pictures to forecast LULC in the Karaivetti wetland. (Zhao et al., 2023) calculated the land price using deep learning. (Campos-Taberner et al., 2020) examined the use of deep learning techniques with remote sensing photos to determine land occupancy for agricultural applications. (Wang & Wang, 2018) explored the relevance of edge computing in addressing the difficulty of detecting lane lines. (Chang et al., 2025) investigated the usage of ESP32 in edge computing, which is a deep learning module used for object detection (Khan, 2025).

(Aslam & Santhi, 2019) investigated the use of convolutional neural networks and deep learning approaches for picture segmentation and computer aided analysis. (Marasinghe et al., 2024) used computer vision technologies to extract information from visual data and improve urban planning. (Wang et al., 2022) explored the role of machine learning in urban planning and agricultural yield prediction. (Zhang & Tong, 2023) employed a deep learning regression model to place the waterline in a converted image.

(Soleimani et al., 2024) suggested a deep learning approach for remote sensing photos that overcomes shifts in urban texturing and hazard damage data. (Mustafa et al., 2024) discussed and evaluated the performance of the usage of artificial intelligence tools like LIME and Grad-CAM for predicting natural disasters. (Hasanuzzaman et al., 2023) discussed the effective utilization of AI tools for weather forecasting as a part of disaster management. (Sun et al., 2020) presented an AI-based decision-making tool for supporting disaster management systems effectively.

(Yu et al., 2022) discussed the use of artificial intelligence to anticipate land degradation based on land use and cover change. (Li & Hsu, 2022) provided an overview of GeoAI for geospatial pictures. (Jafary et al., 2024) suggested a deep learning and machine learning-based value model for regional environmental evaluation in Melbourne Metropolitan, Australia. (Gharbia, 2023) investigated the use of satellite photos and deep learning approaches for water body extraction.

III. RESEARCH METHODOLOGY

Chennai Puzhal Lake's satellite image was obtained from the Bhuvan website, Bhuvan 2D 2.0 (nrsc.gov.in), using a variety of time series that include 2017 and 2021. The training data set consists of the satellite images of Puzhal collected for the year 2015, as shown in Fig. 2, and for the year 2017, as shown in Fig. 3. With a latitude of 13.17 N and a longitude of 80.09, the 2021 satellite image of Puzhal lake is as shown in Fig. 4, is used as test data. As illustrated in Fig. 5, log in to the Edge Impulse program and enter the input data (training and test data). As illustrated in Fig. 6, we must now generate the impulse using the input image processor block and transfer learning as the learning block. The input data type, parameters taken into consideration, processing block, and output features are all stated in the impulse production section of the Edge Impulse software.

Fig. 2 Satellite Image -2015 (Trained Data)

Fig. 3 Satellite Image -2017 (Trained Data)

Fig. 4 Satellite Image -2021 (Test Data)

Fig 5 Trained Dataset in Edge Impulse

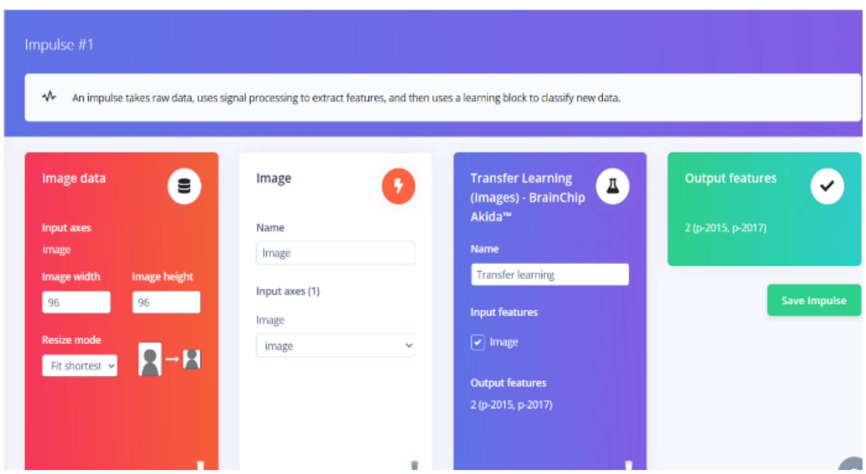

Fig. 6 Creating Impulse in Edge Impulse Software

1. The feature explorer was plotted for the years 2015 and 2017 after the features of the raw and DSP data had been extracted. In the graph, the orange dot represents the feature of the year 2017, while the blue dot represents the satellite image feature of 2015. Fig. 7 illustrates the difference in the feature explorer for the two years.
2. Next, enter the neural network parameters as displayed in Fig. 8. Details regarding the number of training cycles, learning rate, kind of training processor, etc., must be mentioned in neural network settings. As illustrated in Fig. 9, retrain the model and continue with model testing and deployment. Fig. 10 compares the explorer feature of the test data satellite image from 2021 with the trained data from 2015 and 2017.
3. Fig. 11 and Fig. 12 compare the explorer feature of the test data satellite picture from 2021 with the trained data from 2015 and 2017. Flowchart Fig. 13 displays the whole flowchart that explains the algorithm used in this study process.

By understanding the variation in features obtained by comparing test data and train data, the level of land encroachment happened along the banks of the lake can be visualized.

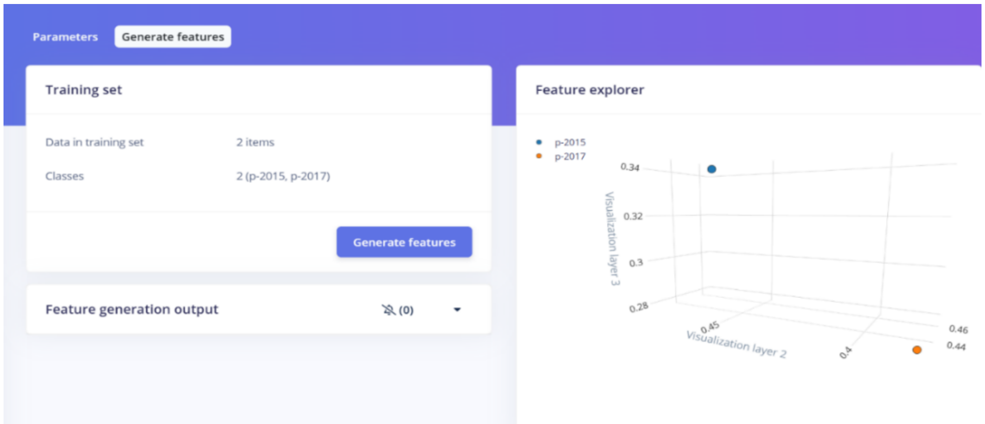

Fig. 7 Generating Features in Edge Impulse

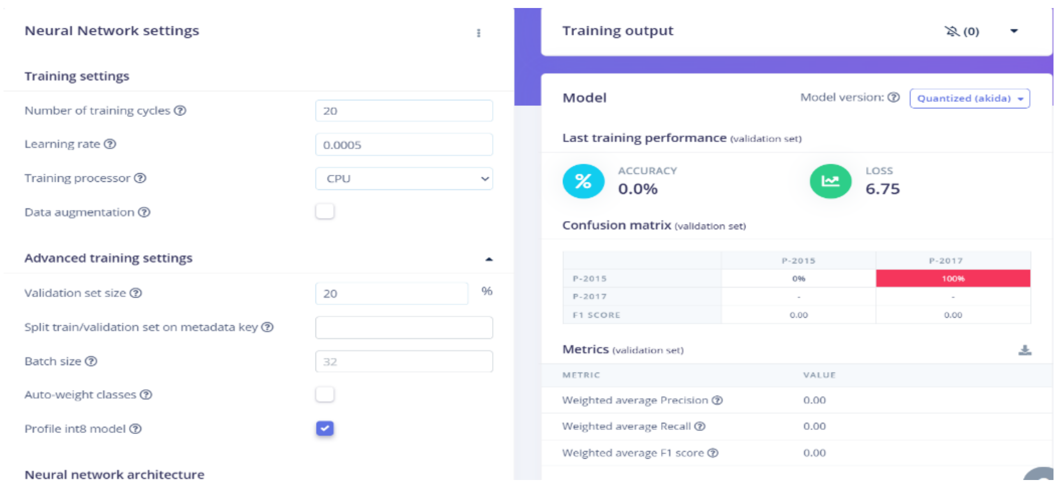

Fig. 8 Neural Network Setting

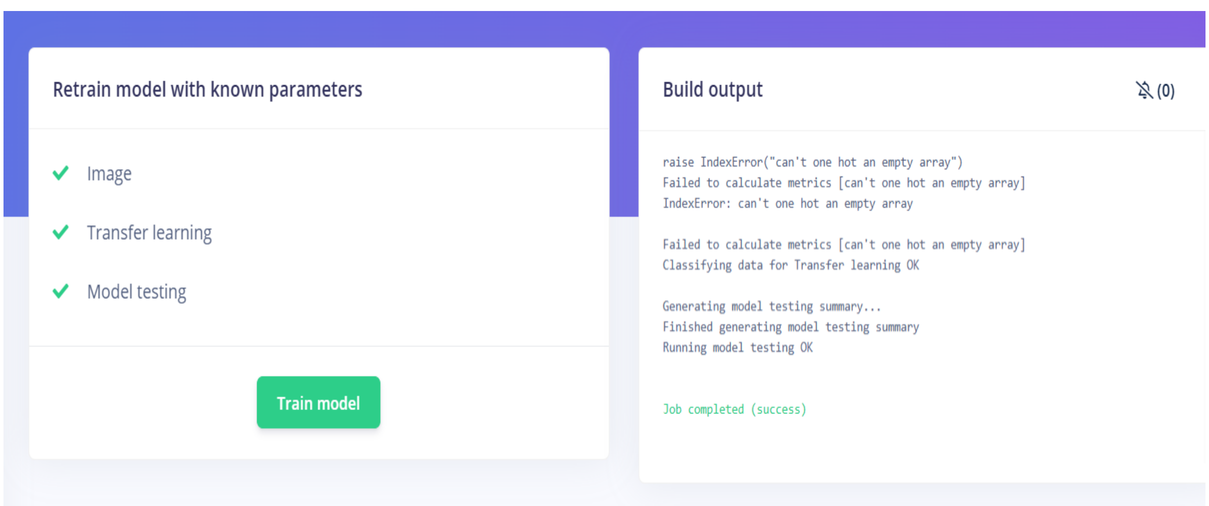

Fig. 9 Retraining the Model with Known Parameters, Network Settings

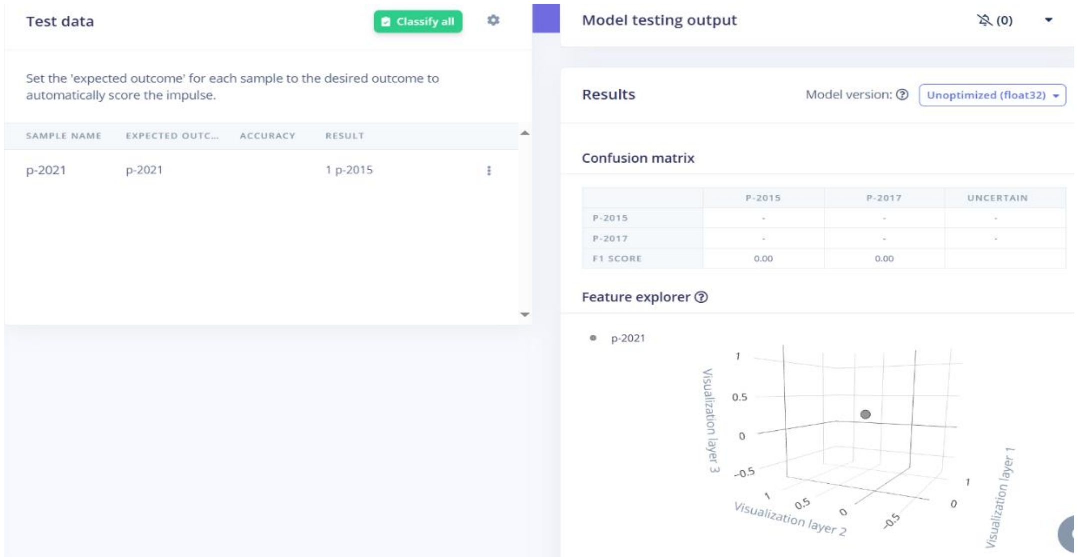

Fig. 10 Generating the Features of Test Data

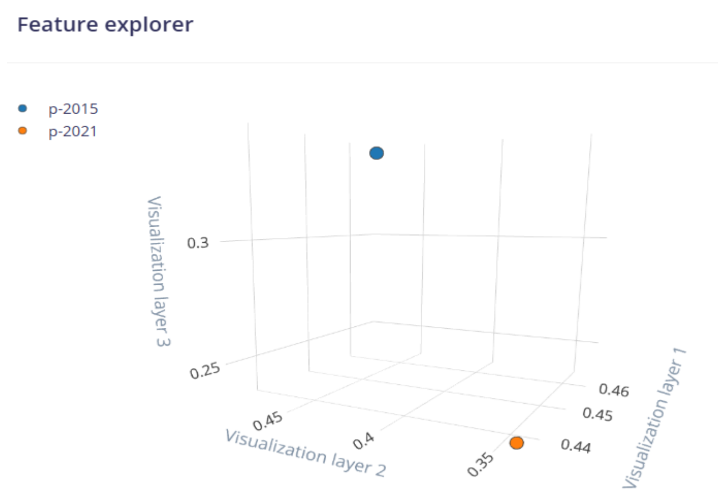

Fig. 11 Feature Explorer of the Satellite Image of the Year 2015 and 2021

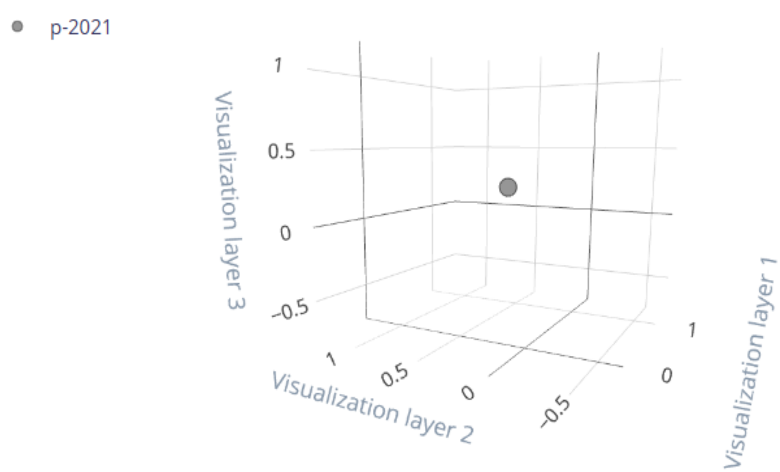

Fig. 12 Generating the Features of Test Data (2021)

The distance between the optimal centroid points between the trained data (for the years 2015 and 2017) and the test data (for the year 2021) shows the level of anomaly in the image. Here in this case is the satellite image for the year 2021. The k-means algorithm is used for anomaly detection in Edge Impulse software. The practical implication of this finding could be one of the effective tools for urban planning and disaster management in major cities, especially in dealing with flood management systems in cities.

Obviously, as stated in the article's abstract, these findings via Edge impulse may also be justified by directly utilizing image processing and anomaly detection using a computer vision code written in Python. After extracting the features of raw and DSP data, the model is deployed following transfer learning, retraining the model, and model testing, as illustrated in the flowchart in Fig. 13, which depicts the complete flow of procedures taken while utilizing Edge impulse for anomaly detection. The processing block utilized here should be k-means anomaly detection in Edge Impulse.

Fig. 11 depicts the visualization layer 1,2 and 3 of the Edge Impulse software, which displays the feature explorer of the satellite images for both 2015 and 2021. This implies that there is a significant difference in the feature explorer over the last two years, implying that some abnormality occurred as a result of land acquisition. Fig. 12 depicts the mean value of a k-means cluster for the year 2021 across visualization layers 1, 2, and 3.

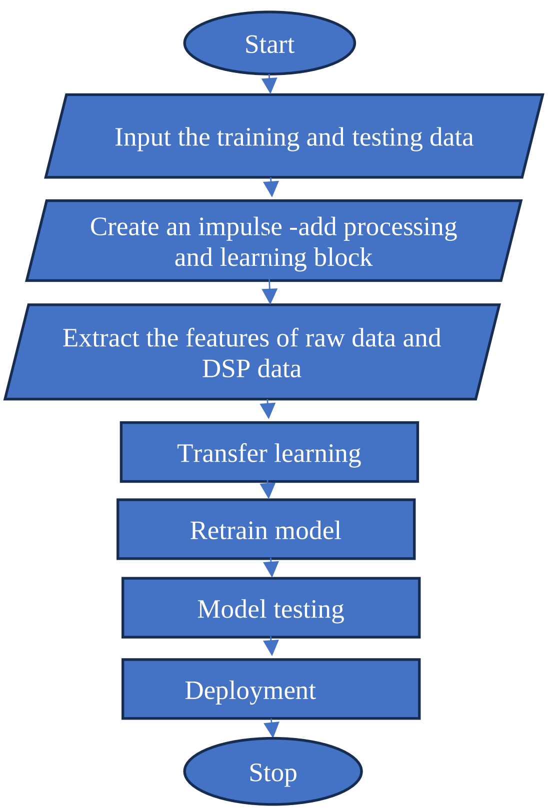

Fig. 13 Flow chart explaining Research Methodology

This method's performance will improve if we use a larger number of input photographs in a variety of periods from 2015 to 2020 as training data. This improves the model's reliability. In this scenario, because we only have two training data points, namely 2015 and 2017, the accuracy level will be lower.

The test data would include any time series data value that occurred after the training data year (i.e., from 2015 to 2017, which is called the reference data). In this scenario, the satellite image for the year 2021 is used as test data, and the anomaly is discovered accordingly.

A. *Identify Anomaly Detection*

Using computer vision to identify the abnormality is the second phase of this research project. Fig. 14 displays the 2021 satellite image of Puzhal Lake, which is then transformed into a grayscale image in Fig.15. Fig. 16 displays the 2015 satellite image of Puzhal Lake, while Fig. 17 displays its grayscale image. This image is first subjected to a bitwise XOR technique, which highlights the differences between the two images. Zero will be the outcome when the pixel of two photographs are discovered to be the same, and when the pixels of two images differ, the outcome will also be 1. Fig. 18 displays the final output image that is produced by performing the XOR operation, and Fig. 19 displays the image that is produced after applying a binary threshold to Fig. 18. By analysing this Fig. 19, the difference in satellite images of 2015 and 2021 is identified, justifying that the land acquisition has occurred surrounding the Puzhal Lake of Chennai city. This alarms the situation and falls as the reason for the recent flood in that area because of the improper urban planning by means of occupying the lake beds. Thus, the rise in the development of computer vision technology has enabled a tool for analysing the anomaly of the satellite images in varied time series to identify the level of land acquisition happening in major cities because of the rise in population.

Fig. 14 Satellite Image of Puzhal Lake in 2021

Fig. 15 Gray Scale Image Converted

Fig. 16 Satellite Image of Puzhal Lake in 2015

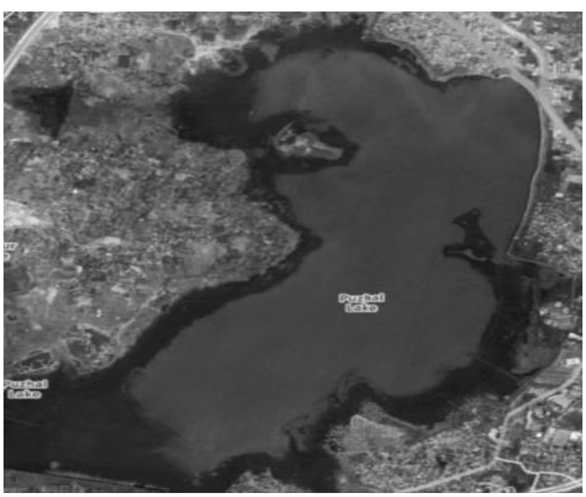

Fig. 17 Gray Scale Image Converted

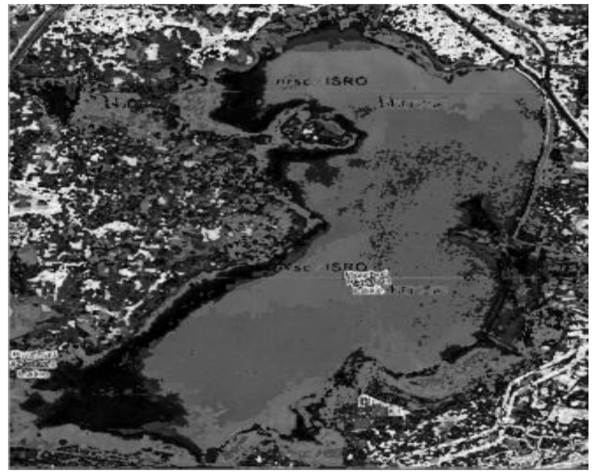

Fig. 18 XOR Output Image

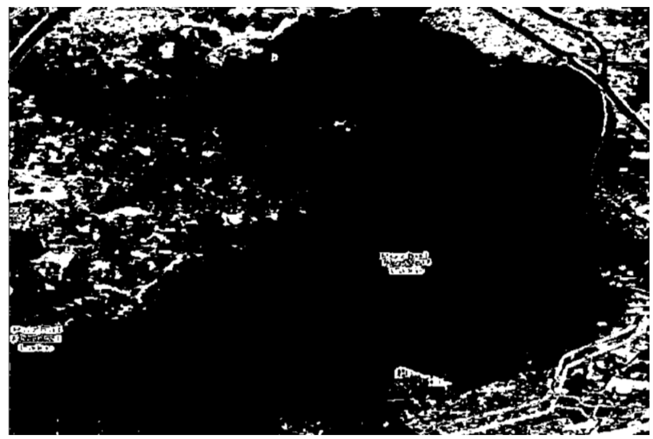

Fig. 19. Image After Binary Threshold

IV. CONCLUSION

As a result, the final graphic displaying the difference in satellite images between 2015 and 2021 shows the anomaly. The robustness of the finding could be improved by using more trained data in the Edge Impulse software. The amount of land acquisition or encroachment surrounding Puzhal Lake during these six years is evident from the white spot, which denotes the discrepancy or anomaly. In the coming years, this severe encroachment will cause the lake to disappear, which would lead to a man-made calamity known as flooding during the monsoon season. The practical implications of the findings are not limited to urban planning but may be used in any study involving the comparison of satellite photos for various time series data, particularly when considering weather forecasting, agricultural growth rate, and so on.

V. LIMITATION

The image comparison was done based on the 2D satellite image from ISRO's Bhuvan software. While taking the satellite images, it is ensured that the sky is clear of clouds at least over the desired location. More number of trainings data (here, only two years of data, 2015 and 2017, is considered as trained data) will result in more accurate and better feature creations which, enhances the anomaly detection in a superior way. The model accuracy could be improved by considering a larger number of input images varying from the years 2015 to 2017 as the trained data. This improvised model accuracy would rather contribute to the potential mitigation strategy in analyzing the anomaly, or in other words, identifying the level of land acquisition for the application considered. Similarly, the robustness of the result obtained considering only two years as trained data would be improved when a greater number of input images across varied time series between 2015 and 2017 are considered as trained data.

VI. Acknowledgment

Need to acknowledge the Edge impulse software for providing this platform to do this project, and also need to thank the ISRO 's Bhuvan 2D platform for supporting in obtaining the input satellite image of Chennai's Puzhal lake at various time scales.

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