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A New Water Level Measurement Technique Using Artificial Intelligent

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Abstract

Flash floods are a growing concern worldwide, causing economic and social losses, increased death rates, and damage to infrastructure. The rapid nature of these disasters has led to delayed and inaccurate flood event information, causing public confusion and delays in response. This study aims to use AI to measure flood levels in real-time to improve flood information during flash floods. In this study, an Axia automobile as a model has been tested in an open space area. Then, box and manilla card is used as a level to mark the height of flood water, which is 15cm, 30cm, and up to 105cm. Data was collected by taking pictures of the vehicle from a distance of 620cm, 720cm, and 820cm. Teachable Machine applications has been used in this experiment to train the model for the data analysis. Image processing methods from the data have been used to identify flood elevation. Key findings show the true percentages and false percentages accuracy of AI measurements on water level and distances measurement. Accuracy of AI measurements for distance represent 80% accuracy for correct value and 20% for the wrong values. Other than that, for accuracy of AI measurements on water level shows 90.5% indicates the accurate percentage and 9.5% indicates the inaccurate percentages. Additionally, the comparison in measuring water level between two devices, which is camera and Iphone show that the camera achieves 87% is accurate meanwhile the Iphone reached 62% of accurate values. Good agreement shows based on findings. However, some areas need to be improved especially for Iphone devices.

1. Introduction

Flash floods are one of the problems of flood disasters and are not a new phenomenon and have long been a serious concern for communities worldwide. In the present time, the intensity and frequency of floods have significantly increased, causing unpredictable and rapidly occurring, especially in urban areas [1]. Rapid urbanization negatively affects the hydrologic cycle and makes cities vulnerable to disastrous flash floods [2]. The emergence of these flood disasters has brought various negative effects, including erosion and water pollution in natural ecosystems, significant economic and social losses within the environment, an increase in death rates and loss of lives, as well as damage to infrastructure and public facilities. Global climate changes have exacerbated such issues, further upsetting hydrologic patterns.

Due to the swift and unpredictable nature of these floods, the dissemination of flood event information has been delayed and inaccurate to convey to the public and surrounding authorities. Delayed or inaccurate information leads to the public being unaware and finding it difficult to identify the flood-prone areas, potentially causing them to pass through such areas. Congestion in traffic management will result from this. Additionally, this delays the rescue team's response time. This study aims to use AI to address the challenge by proposing an innovative assessment methodology to measure flood level in real-time to improve the flood information during flash flood [3].

Water level measurement refers to the elevation above (more common) or below (less common) a reference point established by the user. Since many applications need precise level data, this is one of the factors that is measured the most. There are two ways to assess water levels: AI measurement and manual measurement. Recent years have seen the establishment of several techniques, including deep learning with real-world photos and trained SD processing [4], deep learning regression model and mapping approach [5], and the use of remote sensing, GIS, and in-situ measurement [6]. There are types of water level measurement by using manual measurement. First, this study attempts to reproduce the erroneous water level readings by modeling the reactor, the containment and the water level measurement system, using the MELCOR code version 2.2 revision 15254 [7]. Second, this study is based on the ICESat-2/ATLAS laser altimetry and GEE cloud computing platform for a more thorough assessment of the performance of inland water level and volume changes of the main lakes and reservoirs in the Yellow River Basin [8]. Lastly, the main objective is to quantify the water level from the TG-2 InIRA within small water bodies. Second, assess the accuracy and influencing factors of the TG-2 InIRA derived water levels. Third, explore whether the accuracy of TG-2 observations is sufficient for capturing river gradients, which are critical for characterizing the spatial hydraulics of regional river systems [9]. There are two types of water level measurements using AI. This study addresses these issues, a reliable water level measurement technique [10]. This study is more adaptable to use and implementation in different types of environments [11]. Lastly, this study proposes an advanced, low-cost monitoring system based on deep learning techniques that use staff gauges and camera to extract the water level [4].

Currently, AI technology has been widely employed in various fields. AI is a computer algorithm that learns from data through machine learning, mimics human cognitive abilities, and operates without human intervention. Natural language processing, machine learning, deep learning and other technologies are all included under the broad term AI. There are various studies using AI. First, conceptual in nature and discusses ChatGPT as a generative form of artificial intelligence was proposed that presents challenges for management educators that need to be addressed through appropriate strategies [12]. Besides, the purpose of this study is to bridge the knowledge gap between the literature on management education and AI by highlighting ChatGPT's value as a generative learning tool. Second, for approaching the deliverability of underground characteristic gas capacity (UNGS) in several geographical arrangements, hybrid intelligent models' coordination the slightest square back vector machine (LSSVM), social calculation (CA), hereditary calculation (GA), differential evolution (DE), radical competitive calculation (ICA), instructing learning-based enhancement (TLBO), and molecule swarm enhancement (PSO) were proposed [13]. Third, steps of an interesting DSS framework were proposed and planning to achieve Feasible Advancement Objectives by observing, anticipating, and controlling surges [14].

There is potential to use AI as part of the water level measurement method. First, to address these issues, a reliable water level measurement technique is presented in this paper [10]. The final experimental results show that this study is more adaptable to use and implementation in different types of environments. Second, a low-cost, sophisticated monitoring solution based on deep learning methods that extract the water level using cameras and staff gauges was suggested. This study aims to develop an AI algorithm for flood level measurement in real-time to improve the flood information during flash floods.

Teachable Machine is a Google-developed web-based tool that simplifies the process of training machine learning models using image, audio, or pose data [15]. It is user-friendly, allowing users to capture live data through a webcam or upload files from their system or Google Drive [16]. The tool is based on Google's TensorFlow.js library and employs a Convolutional Neural Network (CNN) for image recognition [17]. It supports rapid prototyping and experimentation, making it ideal for educational purposes and hands-on learning of machine learning (ML) concepts. Teachable Machines have shown effectiveness in various fields, such as crop health monitoring [15], student attendance tracking [16], and teaching machine learning concepts [19]. It also addresses challenges in machine learning, such as data scarcity and variability within disability groups, by offering personalized data training [18]. The tool is designed with usability and privacy, ensuring data remains on the user's device while offering customization options and visualizations for model evaluation [16]. This study aims to use AI to address the challenge by proposing an innovative assessment methodology to measure flood level in real-time to improve the flood information during flash flood [3].

2. Research Methodology

The flood measurement was set up using an Axia automobile that has been tested in an open space area, with minimum object in the background. This experiment was carried out at midday to take advantage of the better light and to prevent any ensuing shadows. The height of the flood water level, which is merely 15cm, 30cm, and up to 105cm, is marked with box or manilla card and tape using it as a level. Pictures of the car and the height of the box or manilla card for the flood water level were taken from a distance of 620cm, 720cm, and 820cm, and the data was recorded. For the experiment, only the silver Axia car was used. From data collection, the sample images of different water levels have been uploaded into Teachable Machine application and then has been developed by one AI algorithm related to the image.

The method of AI used in the Teachable Machine extensively employs neural networks, namely Convolutional Neural Networks (CNN) which learn data patterns. It is used to handle difficult and complex tasks including image, audio and pose recognition. The calibration process was unnecessary as the application is pre-calibrated. The uploaded images are used as training data for CNN, and then processed to determine the percentages accuracy of the measurements. This training step allowed the AI to learn how to recognize and measure varied water levels and distance accurately. Once the model was trained, the application was used to snap the new photos based on the water level and distance specified and generate AI-based measurements of water levels. The AI generated measurements are then validated by comparing them to the actual, measured values, ensuring the model's reliability and accuracy in the applications. The difference has been used to modify AI results until the result is accurate. After modification, another test from different heights has been conducted to check the percentage accuracy of AI measurement. This study uses Teachable Machine applications to get results and run the analysis. Fig. 1 below illustrates the flowchart detailed process methodology of the experiment.

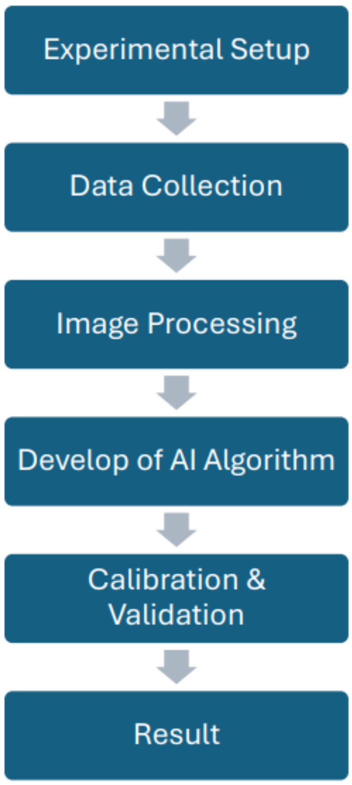

Fig. 1 Research Methodology

3. Data and Discussion

Fig. 2(a) shows the accuracy of AI measurement for distance from camera. The pie chart shows the comparison between AI distance and actual distance has an 80% accuracy rate for correct value. This shows that 80% of the time, the AI system measures the distance correctly. Instead, the table represented by the smaller segment of the pie chart, which is 20% accuracy rate from 100%. For 20% accuracy consists of samples 4b, 5b, 6b, 7b, and 8b, which showed 620cm, 620cm, 820cm, 620cm, and 820cm, respectively, are the five real AI data that are not equal to the actual distance which should be 720cm. However, study lighting, erratic camera position and the small amount of data collected all contributed to the incorrect 20% value error. This analysis found that 80% percentage accuracy of correct value data is greater than 20% wrong value data means the percentage accuracy is acceptable using application Teachable Machine.

Fig. 2(b) illustrates the proportions of true and false accuracy in the AI system's water level predictions. The larger segment, representing 90.5%, indicates the percentage of accurate predictions made by the AI system. The smaller segment, representing 9.5%, indicates the percentage of inaccurate predictions made by the AI system. Based on the pie chart, one significant factor that may have influenced the accuracy is data quality. A high true accuracy rate can be obtained by using wide-ranging, accurate and high-quality data to train the AI prediction. Conversely, any errors or inconsistencies in the data could contribute to the false accuracy percentage. Overall, the chart suggests that the AI system has a high accuracy rate in predicting water levels, with most of its predictions being correct. Consequently, the pie chart indicates that the percentage of AI water level is more acceptable since most of the sample matched the actual water level.

Fig. 2(c) and (d) show the comparison between the accuracy of AI systems in measuring water levels using two different devices, which is a camera and iPhone (IP) device. The AI measurements were compared to actual water levels, showing that the camera achieved 87% is accurate and only 13% is false. Meanwhile, the Iphone reached 62% of the measurements is true and 38% is incorrect as shown in pie chart below. The lower accuracy may be attributed to various factors such as differences in sensor quality, environmental factors like variations in lighting and object backgrounds, and also camera instability. Although the Iphone still provides reasonably reliable measurements, it requires further calibration to achieve higher accuracy. Therefore, this difference shows that the Iphone's accuracy percentage is less acceptable compared to the camera, which proves to be more accurate and reliable.

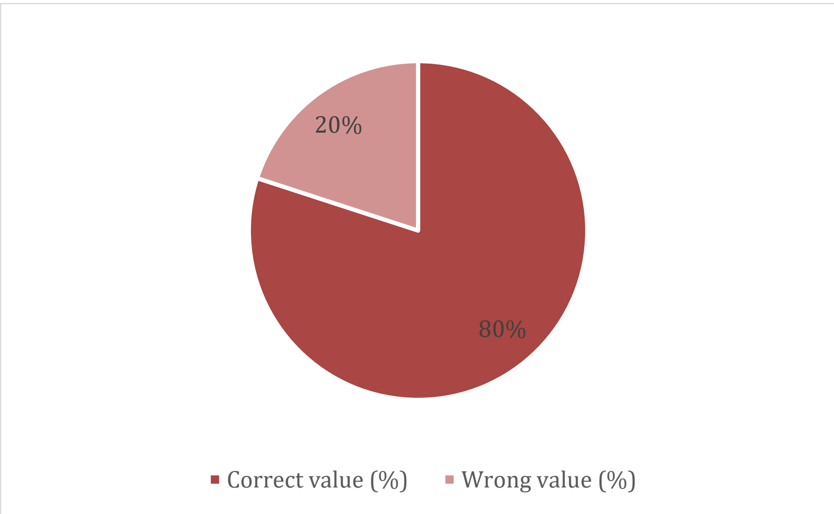

Fig. 2(a) The Accuracy of AI measurement for distance from camera.

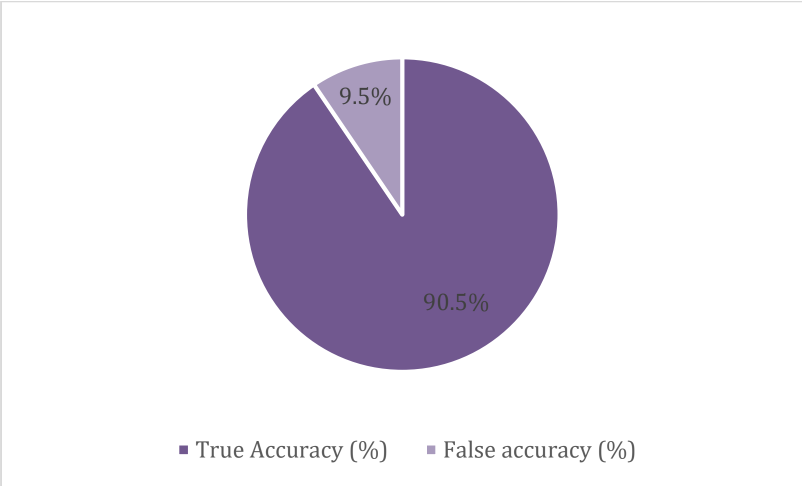

Fig. 2(b) The Accuracy of AI for water level

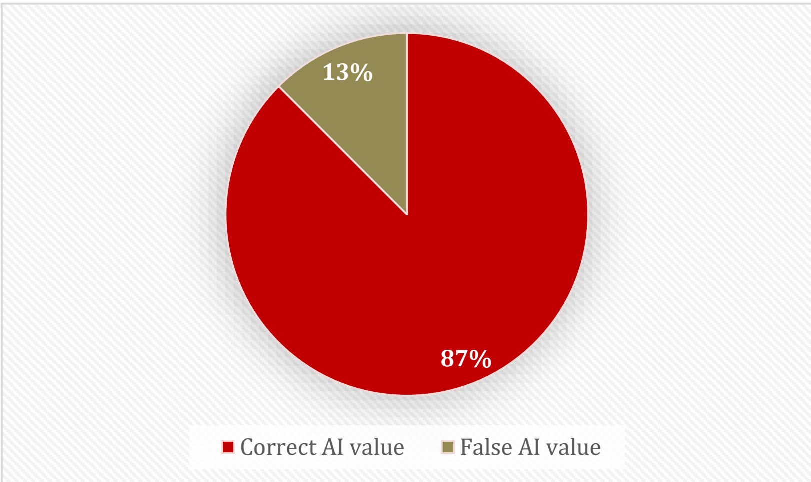

Fig. 2(c) The Accuracy of AI Measurement for Water Level from Camera using Logitech Camera

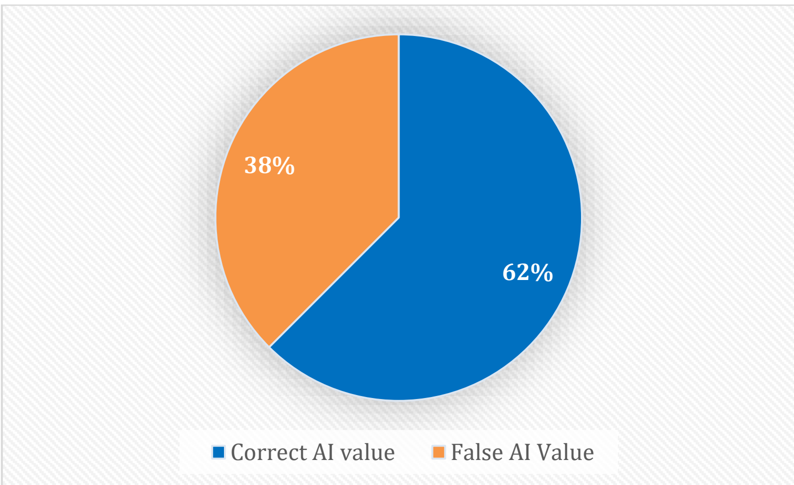

Fig 2(d) The Accuracy of AI Measurement for Water Level using Iphone 11 Pro Max

Based on Fig. 3(a) and (b) below, the AI's accuracy in measuring water levels and distances compared to random values was evaluated using a camera. This analysis aims to determine the accuracy of AI when measuring random values compared to the actual values. Water level and distance values are used instead of actual measurements to test the AI application's accuracy and to see if the AI remains reliable despite random inputs. Both pie charts below show a highly inaccurate, with 100% of the measurements being false. The high percentage of inaccuracy values are due to several factors: insufficient training data which is the AI model not been exposed to enough range of dataset, where there is no dataset on random values that has been uploaded into the application. External factors such as lighting, shadows and background changes also affect the accuracy of measurements. To improve the AI's accuracy in this case, several solutions should be considered. Increasing the dataset by collecting a more extensive and varied set of training data, including various water levels and distances under different conditions. Besides that, improvements in environmental factors such as minimizing shadows, background and maintain a fixed camera angle and position to ensure consistent measurements. Additionally, the AI model requires better calibration and validation to align training data with actual data. Overall, this accuracy level is unacceptable due to the high inaccurate percentages and can lead to significant errors and potential risks.

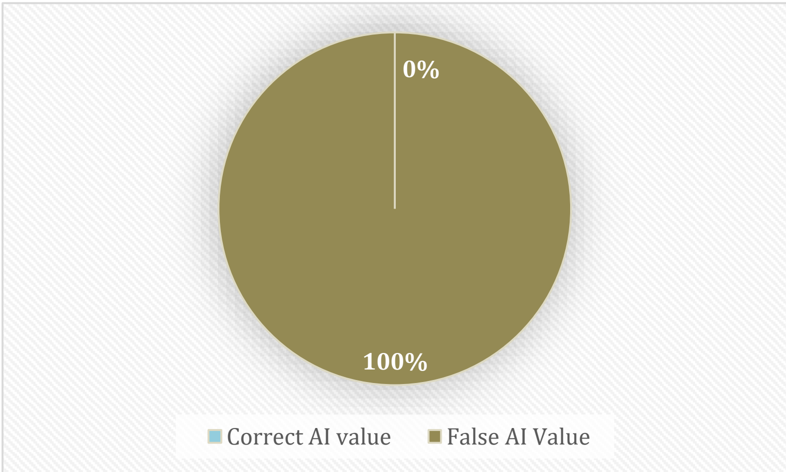

Fig. 3(a) The Accuracy of AI Measurement for Random Water Level

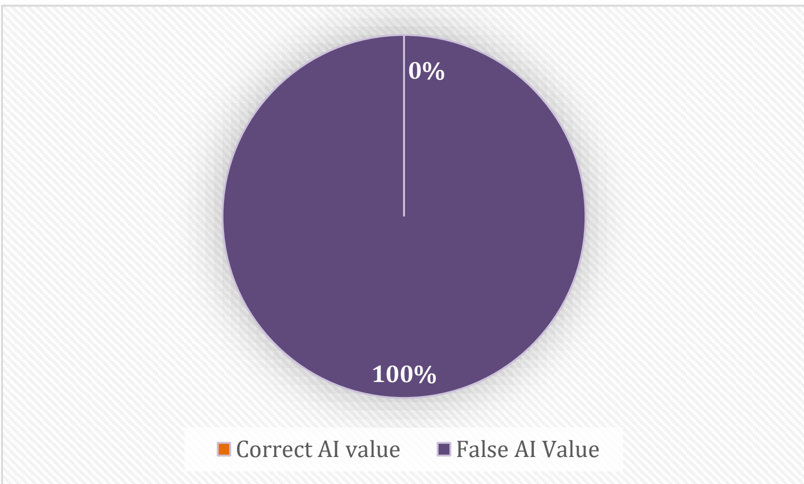

Fig. 3(b) The Accuracy of AI Measurement for Random Distance from Camera

4. Conclusion

Teachable Machine is a machine learning tool that classifies images based on data collected from experiments, model training, and evaluation. It uses Convolutional Neural Networks (CNN) in TensorFlow.js to process data in a web browser, making it accessible on various devices. The trained model is tested with new images to assess accuracy, highlighting the difference between actual and AI-generated data. In this experiment, the Teachable Machine has been used to determine the depth of rising water and distance from a camera to a car. Sample images of water levels and distances have been uploaded, and the AI model has been trained to recognize distance and accurately measure varied water levels. The accuracy of the measurements has been validated by comparing the AI-generated data with actual measurements and AI measurements. This experiment used 4 data obtained to find out the level of accuracy using pie chart of these Teachable Machine.

The first pie chart is the accuracy of AI measurement for distance from camera showing 80% correct value is greater than 20% wrong value. Second, pie chart shows the accuracy of AI water level is 90.5% correct value and 9.5% is wrong value from application Teachable Machine. Third, pie chart shows the comparison between the accuracy of AI systems when measuring water levels using two different devices, it was found that camera had more correct value percentages of 87% compared to using the iPhone by 62%. The last one is accuracy of AI in measuring water level and distance compared to random values from camera shows error or inaccuracy with 100% of the measurements being false value in pie chart. Based on the data and analysis, the Teachable Machine apps are more accurate when determined water level measurement compared to distance measurement. Additionally, measuring water levels and distance measurement with a camera is more reliable than using an iPhone.

Machine learning applications can improve data accuracy by capturing images from various angles and perspectives, including vehicle color, different car models, and sizes. Clear and bright images are essential for ensuring accurate information. In Teachable Machine apps, clear images are crucial to avoid blurry images, which can obscure important details and reduce the model's ability to learn accurate patterns. Capture photos against a plain backdrop or open space, and regularly test and assess the model to identify any changes over time. Regular testing and assessment will help determine the best enhancements for smooth operation of the application.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Iely Maisara binti Ibrahim, Nur Aisyah Jamilah binti Alias, Siti Najihah Umairah binti Ngatalin, Muhammad Azraie bin Abdul Kadir;* ***data collection:*** *Iely Maisara binti Ibrahim, Nur Aisyah Jamilah binti Alias, Siti Najihah Umairah binti Ngatalin, Muhammad Azraie bin Abdul Kadir;* ***analysis and interpretation of results:*** *Iely Maisara binti Ibrahim, Nur Aisyah Jamilah binti Alias, Siti Najihah Umairah binti Ngatalin, Muhammad Azraie bin Abdul Kadir;* ***draft manuscript preparation:*** *Iely Maisara binti Ibrahim, Nur Aisyah Jamilah binti Alias, Siti Najihah Umairah binti Ngatalin, Muhammad Azraie bin Abdul Kadir. All authors reviewed the results and approved the final version of the manuscript.*

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