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AQUAFAZE: AN AI-ENABLED FACE-IMAGE-BASED WATER REQUIREMENT PREDICTION

Usha Rani Gogoi[1*], Subhodeep Ghosh[1,2], Madhu Sudan Das[1]

[1]Department of Computer Science & Engineering, The Neotia University, Diamond Harbour, Kolkata, West Bengal, India,
[2]Chief Technical Officer (CTO), Group of Blooming Technicians, Kolkata, West Bengal, India,
Corresponding Author: ushagogoi.cse@gmail.com

Abstract
Staying hydrated is essential for maintaining overall health and wellbeing. Water constitutes a significant percentage of body weight. Staying properly hydrated is important for various physiological functions and has a range of health benefits. Therefore, it is important to consume an adequate amount of water daily. However, the specific needs of an individual may differ depending on the factors like age, gender, ethnicity, height, weight and the activity level. Even after knowing the importance of water intake, people do not take sufficient water, for which people suffer in dehydration where the body suffers from electrolytes imbalance and a reduction in blood volume. Dehydration, in severe cases, can also lead to heat exhaustion and heat stroke. Considering the importance of staying well hydrated, this work emphasizes on designing a Single face image-based Artificial Intelligence (AI) enabled water requirement prediction system, AQUAFAZE, where the user only needs to turn on his/ her device camera to predict the water requirement for that day. The proposed system can predict the age, gender, ethnicity, weight and height of an individual from the face image, and then using all these parameters, it predicts the hydration requirement of that person. In addition, the proposed system also predicts the excess water requirement for performing various activity for a certain duration. In absence of any such AI enabled single face image-based hydration prediction system, the performance of the proposed AQUAFAZE is compared with the conventional hydration prediction system, where a user needs to enter his/her age, gender, height and weight and based on that the system predicts some results. The comparative study also concludes that the proposed AQUAFAZE system can accurately predict the hydration requirement of a person from a single face image.

Keywords: Hydration requirement, single-image based hydration prediction, Machine Learning, Deep Learning, Activity based hydration prediction;

INTRODUCTION

Water is a vital constituent of blood, which carries waste from the body and provides cells with oxygen and nutrition. Good hydration is one of the most important aspects of the diet. Drinking enough liquids to keep the fluid levels in the body topped up helps to ensure that all bodily functions are able to take place as normal [1]. Having enough water every day helps to maintain normal body temperature, lubricate joints, prevent infections, deliver nutrients to cells, and maintain organ functionality [2]. Additionally, being hydrated enhances mood, cognition, and sleep [3]. Even after knowing the importance of water intake, people do not take sufficient water, for which people suffer in dehydration where the body suffers from electrolytes imbalance and a reduction in blood volume. Dehydration has many effects on the human body and can be very detrimental. Some of the common symptoms of dehydration are fatigue, dizziness, headaches, dry mouth and throat, dark urine, a lower urine output, and a fast heartbeat etc. In addition, dehydration can have a significant effect on mental performance, cognitive function, mood, and decision-making. Memory, attention, and reaction time can be affected by even mild dehydration. Dehydration, in severe cases, can also lead to heat exhaustion and heat stroke [4]. Despite of the potentially dreadful consequences of dehydration, there is an alarming indifference towards its severity. Many people underestimate the risks associated with not drinking enough water. This lack of awareness and casual approach to proper hydration is concerning and can have negative impact on people's health. The consequences of this indifference are far-reaching.

In order to address this issue, it is essential to increase awareness about the importance of hydration and its adverse consequences. Public health messages, workplace attempts, and educational campaigns ought to emphasize the significance of regular fluid intake and provide beneficial suggestions for staying hydrated. By establishing a culture that values and prioritizes hydration, we can work towards reducing indifference, promoting optimal health and performance, and reducing the sufferings that dehydration causes to people and society. With the advancement in technology, a number of systems have been designed to predict the water requirement for an individual. However, for predicting the water requirements, almost all these systems require users to input their basic details like age, height, weight, etc. But, due to the lack of information about height, weight etc. very few people will use these systems. Moreover, the drinking water requirement not only depends only on age or weight, or height, but also on parameters like gender [5, 6] and ethnicity [7]. Despite the importance of these features in predicting the drinking water requirement, there is no such system that predicts all these parameters from a single user's face image. So, considering all these limitations of the existing systems, in this work our key objective is to design a single face image-based AI enabled water requirement prediction system where the user only needs to turn on his/ her camera. Using the potential of machine learning (ML) algorithms, we have designed a system that can predict an individual's age, gender, ethnicity, weight and height from his/her face image to predict the water requirement. People who have no idea about his ethnicity, height or weight can also use this system. The detail of the proposed methodology will be discussed in Section 3 of this paper.

Contributions of the paper are as follows:

a) To the best of our knowledge, this is the first AI enabled approach where we predict the bodily water requirement of a person based on his/ her face image. We termed this system as AQUAFAZE, the Quick analysis.

b) To prove the efficiency of our proposed system, the predicted result of the quick analysis system is compared with the detailed analysis system, where the water requirement of the same person is predicted based on his/her manual input.

c) The proposed system is also capable of predicting the change in drinking water requirement based on the physical activity he/she is going to perform for a particular time period.

The remaining of the paper is organized as follows. Section 2 provides a brief literature survey on the various parameters impacting the bodily hydration requirement. In Section 3, we provide a detailed overview of our proposed AQUAFAZE: the quick analysis system that uses the face image to predict the drinking water requirement. In Section 4, we discuss our experimental results and also compare the performance of our proposed Quick analysis system with the result of the Detailed analysis system which takes all user inputs to predict the drinking water requirement. Section 5 concludes the paper with the future scopes.

2. LITERATURE SURVEY

For optimal health and wellbeing, it is crucial to understand the body's hydration requirement.

Several studies have been made to determine the factors influencing the hydration needs and adequate water intake. Here is a brief overview of key findings from the literature.

The need for water can be greatly affected by age because of changes in physiological processes, metabolism, and body composition [8, 9]. Like age, the water intake varies in male and female.

he National Academies of Sciences, Engineering, and Medicine [10] recommends that men and women should drink roughly 3.7 Liters (125 ounces) and 2.7 Liters (91 ounces) of water daily respectively in addition to all other liquids and meals. European Food Safety Authority (EFSA) also suggested the same amount of water intake for male and female daily in total. The impact of ethnicity is also considerable in water intake prediction. Some factors like cultural practices, food habits, geographic locations, health conditions related to different ethnic group may impact the amount of water intake. Ethnicity may influence the food habits as traditional diets can vary significantly among ethnic groups, affecting overall fluid intake. While determining one's hydration requirement, weight has a significant impact. Weight is one of the important factors that influences how much water a person should drink each day. Since height of a person also impacts the body weight, hence height is also an influencing parameter while predicting the water requirement.

3. PROPOSED METHODOLOGY

The proposed methodology is basically comprising of a pipeline of seven distinct ML models which is named as AQUAFAZE: the Quick analysis as it predicts the bodily hydration level of a user from his/ her face image. However, to validate the result of the proposed AQUAFAZE: Quick analysis model, we have also implemented an AI enabled detailed analysis system that takes the user inputs like age, gender, ethnicity, height and weight to predict the hydration requirement of a person. Each of these Quick analysis and Detailed analysis systems are elaborately described below. Based on the quick analysis result, the proposed AQUAFAZE system is also capable of predicting the excessive hydration requirement for different types of activities.

3.1. Experimental databases

3.1.1. UTK Face Dataset

UTK Face [11] is a large-scale face dataset with a wide age range from 0 to 116 years old. The dataset comprising of over 23,709 face images annotated with age, gender, and ethnicity. The dataset is a challenging dataset as it includes images with large pose variations, facial expressions, illumination and occlusions etc. The dataset contains the faces of people with different ethnicity. The age distribution of the UTK Face dataset is illustrated in Figure 1.

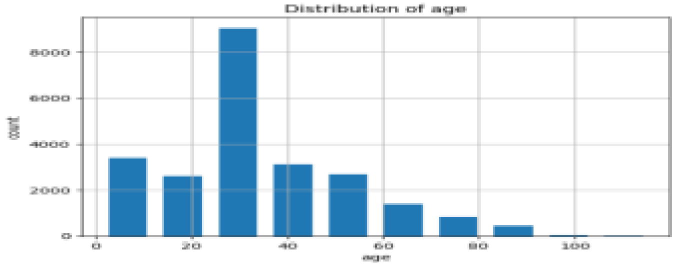

Figure 1. The age distribution of different people in UTK Face dataset

3.1.2. Height Dataset

A municipality health centre dataset was collected and after going through several data pre-processing like handling missing values, discarding of redundant data, dropping of samples where majority of features are having null values, the final experimental dataset was created. Multiple surveys were also conducted in offline and online mode to collect more data and added with the dataset for diversification and verification purpose. This experimental dataset is comprising of 4 features: age, height, gender and ethnicity. The dataset comprising of the data of 200654 samples.

3.1.3. Weight Dataset

A municipality health centre dataset was collected. To increase the size of the dataset, several surveys were also performed to collect more real-time data and it also diversifies the dataset. The dataset comprising of 4 features namely gender, ethnicity, height and weight of 177936 individuals. The distribution of data based on ethnicity and weight is plotted in Figure 2.

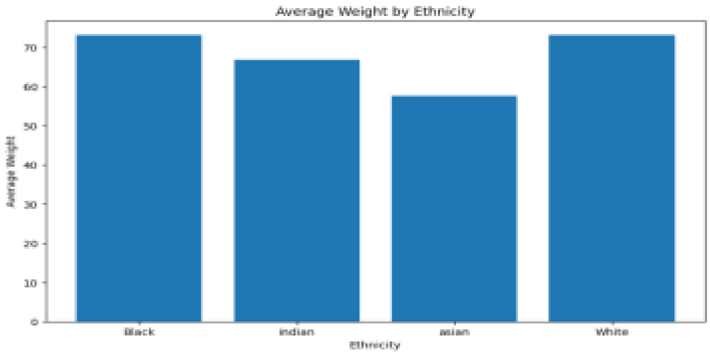

Figure 2. The distribution of weight in individuals of different ethnicity

3.1.4. Hydration prediction Dataset

This is an inhouse dataset comprising of 760 samples' data containing 6 parameters: "age," "gender," "ethnicity," "height," "weight" and "hydration." The age values range from 6 to 100 years. The height and weight values range from 87.51 cm to 194 cm and from 20 kg to 90.6 kgs respectively. The values in the hydration column ranges from 1.11 to 4.39 liters, with a mean of 3.01 liters.

3.1.5. Activity Dataset

This is a dataset with 1741 entries, delves into the intricate connection between daily activities, basic hydration needs, and additional water intake. It dissects four distinct activity types – outdoor sports, indoor routines, desk jobs, and laborious tasks – assigning each a base hydration level (1.01-4.99 Lt). Pairing this with activity duration (1-10 hours) paints a personalized picture of water requirements. Intriguingly, the dataset also captures the "excess hydration," the recommended additional water beyond the base, ranging from 0.00 to 0.5 liters.

3.2. The proposed methodology AQUAFAZE: Quick Analysis

Considering the importance of individual parameter in water requirement prediction, our proposed quick analysis system consisting of a pipeline of seven distinct ML models to predict various aspects related to bodily hydration requirements. The list of seven ML models includes a) Face detection, b) Age prediction, c) Gender Prediction, d) Ethnicity prediction, e) Height prediction, f) Weight prediction, and g) Hydration requirement prediction. The overview of our proposed 'Quick Analysis" phase is illustrated in Figure 3. As demonstrated in Figure 3, the system will take the user input captured through the device camera from which the face will be detected and the face region will be extracted by discarding the background. From the detected face region, the parameters like age, gender and ethnicity will be predicted by using three different ML models. Based on these predicted age, gender and ethnicity, the height of the individual will be predicted by the height detection model and this predicted height along with the predicted gender and ethnicity will be fed to the weight prediction model to predict the weight of the individual. Using these predicted parameters, age, gender, weight, ethnicity and height, the hydration prediction model will predict the water requirement of that particular person. By considering the predicted water requirement of a person along with the input: activity type and activity duration, the "Activity based Excess Hydration prediction model" can predict the excess hydration requirement to perform a certain activity for a particular duration. The details of each of the phases of the proposed quick analysis system is discussed in the following subsections.

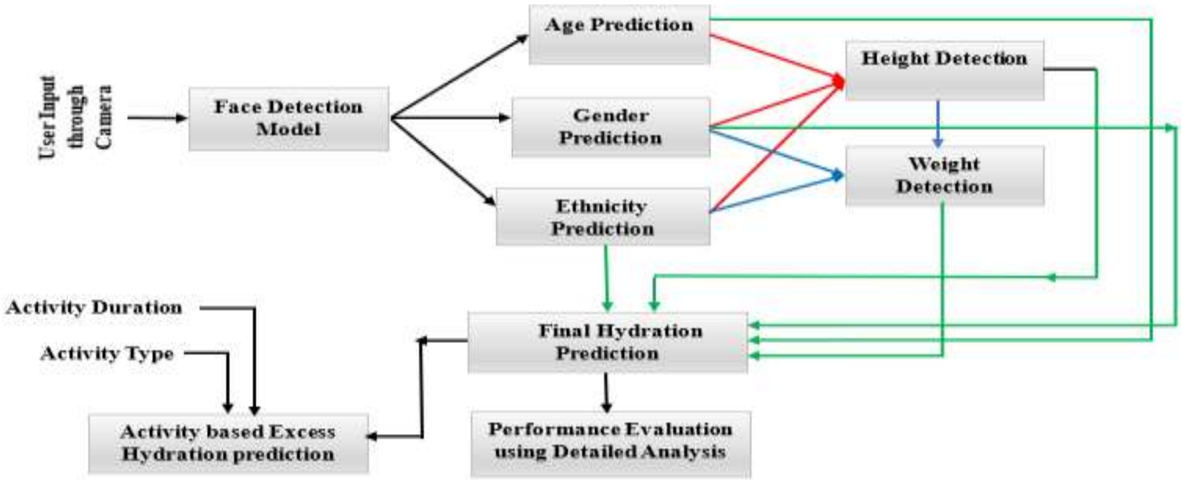

Figure 3. The workflow of the Proposed Face based Quick Analysis system.

3.2.1. Face Detection Model: The objective of the face detection model is to detect the face from the user input image provided through the system's webcam. If user provides any image containing no face, then the model will ask the user to provide a face image. For detection of the face, the performance of three most widely used deep models namely DeepFace [12], YOLO [13], and RetinaNet [14] have been evaluated. The performance of each of these models are provided in Table 1 of the Result and Discussion section. If the input image is a face image, the model extracts the face region from the image by discarding the unnecessary portions of the image. For the experimental purpose, the images of the UTK_Face [11] database have been used.

3.2.2. Age Prediction Model: The detection of face region was followed by the age prediction, as consideration of age is also important for the water intake prediction. The performance of four different models namely, Customized Sequential model-1 (CUSTOM1), Customized Sequential model-2 (CUSTOM2), customized Face-net (CUSTFace_Net) and VGG_Face [15] have been evaluated on the UTK_Face database. As reported in Table 1, out of all these four models, CUSTOM1 provided the highest accuracy in age prediction. The architecture of the CUSTOM1 model is provided in Figure 4. As illustrated in Figure 4, the CUSTOM1 comprising of 3 convolution layers (32 filters in first, 64 filters in 2nd and 128 filters in 3rd layer), 3 max pooling layers, two dense layers and 1 flatten layer. As shown in Figure 4, this architecture predicts both Gender and age of a person. But, unlike the age, the performance of CUSTOM1 in gender prediction is very poor, for which we consider only the age output of this model.

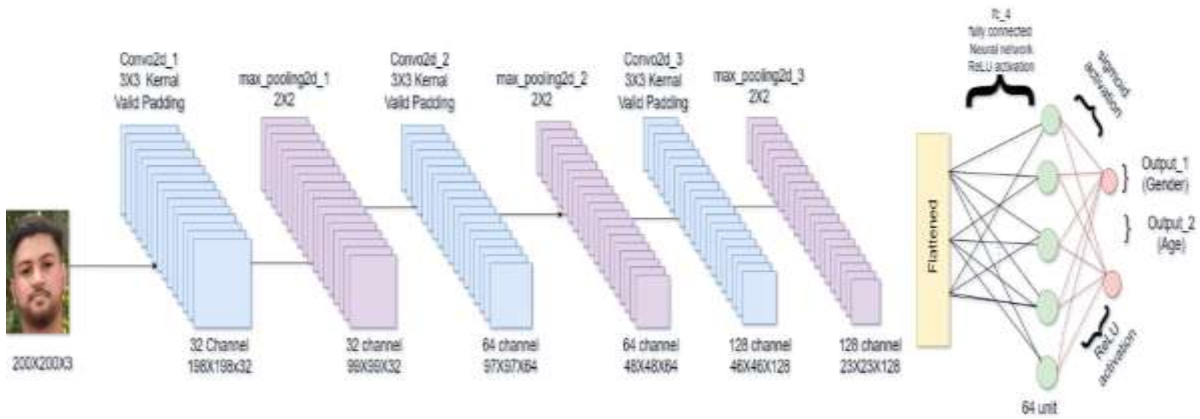

Figure 4. The architecture of the Customized Sequential model-1 (CUSTOM1) for age prediction

3.2.3. Gender Prediction Model: Like the age, the gender also has a significant impact on the water intake, for which in our proposed work, the prediction of age is followed by the prediction of gender of the individual. For designing of the gender prediction model, the grayscale images of the same UTK_Face [11] database are used. For obtaining the highest training accuracy with the experimental data, the performances of three different deep convolution neural networks: CUSTOM2, Inception [16] and CUSTFace_Net have been evaluated. Out of all these three models, as reported in Table 1, the highest accuracy is obtained with the CUSTOM2. As demonstrated in Figure 5, the proposed CUSTOM2 model is comprising of 4 convolution layers (32 filters in first, 64 filters in 2nd, 128 filters in 3rd layer and 256 filters in 4th layer). For pooling, we have used Max pooling. As shown in Figure 5, this architecture predicts both Gender and age. But, unlike the gender, the performance of CUSTOM2 in age prediction is 83.05% only, for which we consider only the gender output of this model.

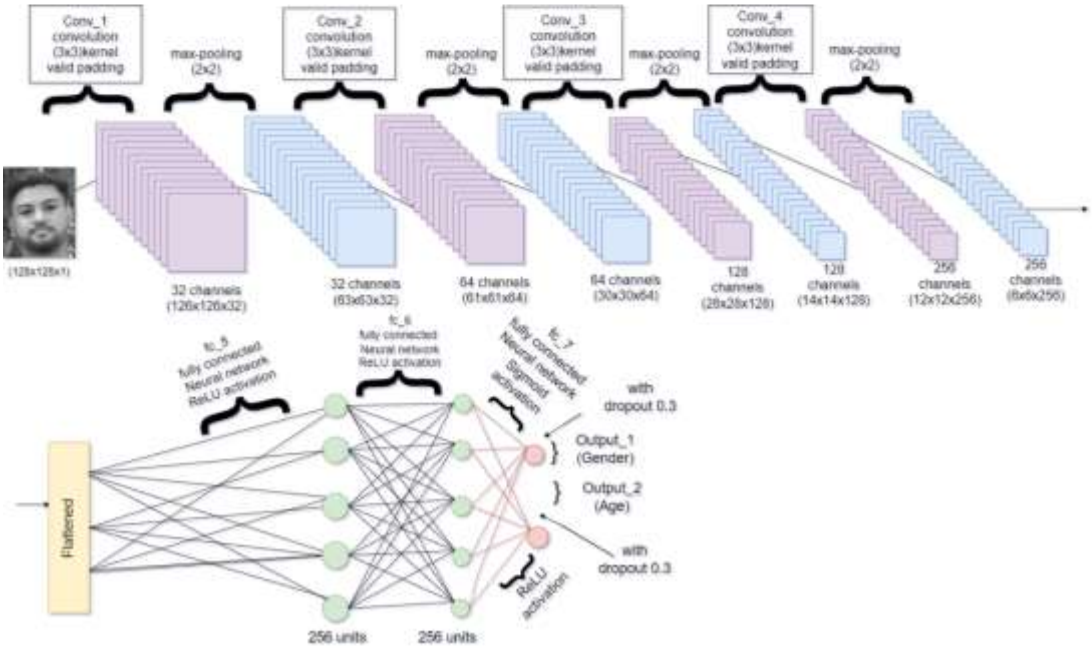

Figure 5. The architecture of the Customized Sequential model-2 (CUSTOM2) for Gender prediction

3.2.4. Ethnicity Prediction Model: Detection of gender is followed by the ethnicity detection for which two deep convolution networks namely Deepface [12] and CUSTFace_Net models have been applied on the UTK_face dataset. Out of these two models, the highest classification performance is obtained with customized CUSTFace_Net model. The architecture of the CUSTFace_Net is illustrated in Figure 6. As depicted in Figure 6, the CUSTFace_Net model comprising of 3 convolution layers (16 filters in first, 32 filters in 2^{nd} and 32 filters in 3^{rd} layer), 3 max pooling layers, two dense layers and 1 flatten layer.

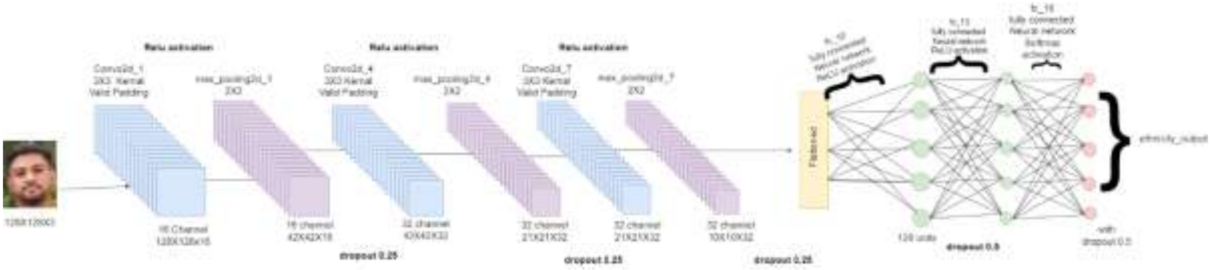

Figure 6. The architecture of Customized Face Net (CUSTFace_Net) for Ethnicity Prediction

3.2.5. Height Detection: Prediction of ethnicity, gender and age from the face image is followed by the prediction of the height of a person based on these parameters. To predict the height of a person from the age, gender, and ethnicity, it is crucial to build a height prediction model. For designing a height prediction system, an experimental dataset comprising of the data of 200655 samples was used. The height prediction performance of various ML models including Support vector regressor (SVR), Decision Tree (DT), Random Forest (RF), Linear Regression (LR) and Xtreme Gradient Boosting (XGB) regressors have been evaluated. The performance of each of these models are reported in Table 1.

3.2.6. Weight Detection

For predicting the weight of a person from a single face image, it is very crucial to train a weight prediction model based on the parameters like height, gender and ethnicity predicted from the face images. The performances of five different regressors including SVM, DT, RF, LR and XGB models have been evaluated to obtain the highest weight prediction accuracy. The performance of each of these models are reported and compared in Table 1.

3.2.7. Bodily Hydration Prediction

Once the age, gender, ethnicity, height and weight of the person are predicted from the face image, next task is to train a model to predict the hydration requirement based on these parameters. The age, gender, weight, height and ethnicity are provided as input to the ML model and as a result hydration requirement is predicted. The performance of five different regressors including SVM, DT, RF, LR and XGB are evaluated. Out of all these five regressor models, DT provided the highest prediction accuracy in Hydration prediction.

3.2.8. Activity based Hydration requirement prediction

Unlike other system for hydration requirement prediction, the proposed system also takes into account the activity that the person is going to perform for a certain duration. Here the term activity indicates playing of cricket for certain duration, walking for certain duration etc. Since, these activities has certain impact on the bodily water requirement, hence in our proposed system we have also incorporated these parameters. A ML based system is designed to predict the water requirement to perform these activities. An experimental dataset comprising of parameters like activity type, hydration type and time duration performing this activity is used to train the model.

3.4. Detailed Analysis

To validate the hydration prediction result of the single image based quick analysis, we have also designed a conventional system for detailed analysis. In the conventional detailed hydration analysis, users will encounter a straightforward online form collecting essential information, such as age, gender, ethnicity, height, and weight. After completing the form, based on these parameters, a 'Hydration Prediction Model,' has been designed using decision tree. The designed model calculates the user's daily hydration requirement in Liters. This personalized recommendation empowers individuals to understand how much water they should aim to drink daily, helping them to stay properly hydrated for improved well-being.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Evaluation metrics

As described in the methodology section, our proposed hydration requirement prediction system, AQUAFAZE incorporates a pipeline comprising of seven distinct ML models. In each phase of the AQUAFAZE system, the performances of more than two models have been evaluated to obtain the highest accuracy for a particular task. However, to make an unbiased comparison of the ML models, we consider model accuracy as well loss for the deep learning models; and prediction performance and error of the regression models. The value of each of these parameters for different models are illustrated in Table 1.

4.2. Performance Evaluation

The performance of all the ML models used in different phases of the pipeline is provided in Table 1. As reported in Table 1, out of all three face detection models, the DeepFace provides the highest face detection accuracy of 92.32% and loss of 0.75. Similarly for age detection, out of four models, the CUSTOM1 model provides the highest accuracy of 89.62% with loss 0.2329 in age detection from the face images. The highest accuracy of 96.61% with loss of 0.0825 is obtained with the CUSTOM2 model in gender detection. For ethnicity detection, we have evaluated the performance of two DL models: DeepFace and Face-net-Custom2, out of which Face-net CUSTOM2 provides the highest accuracy of 82.14% and loss 0.63. For obtaining the highest performance in height detection, the performance of five ML models: SVM, DT, RF, LR and XGB have been evaluated. The experimental results showed that DT is more accurate in height detection providing the R-squared score of .8974. The height detection is followed by the weight detection. The performance of five ML models: SVM, DT, RF, LR and XGB are evaluated and the highest R-squared score of 0.9721 is obtained with DT. Selection of the best ML model for each of the phases of the Quick analysis is followed by the prediction of these parameters from the user input face image. Then based on these predicted parameters, the Main hydration detection model has been designed by using five ML algorithms: SVM, DT, RF, LR and XGB. As reported in Table 1, the face image-based hydration detection model provides the highest R-squared score of 0.9922 with DT algorithm. By considering the output of the quick analysis and by taking the input like: activity type and activity duration the excess hydration requirement has been predicted. As reported in Table 1, the proposed activity based excess hydration prediction system obtained the highest prediction score of 0.9176 with SVR.

Table 1: Comparison of the performances of various ML algorithms in face detection, age prediction, gender prediction, ethnicity prediction, height prediction, weight prediction, and Main hydration detection.

Model name	Method	Dataset	Perfomance	
			Accuracy (%) / R-Squared	Loss/ MAE
Phase-I Face detection	DeepFace	UTK_Face	**92.32**	**0.75**
	YOLO		89.45	1.34
	RetinaNet		90.25	0.898
Phase-II Age Detection	Sequential custom 1	UTK_Face	**89.62**	**0.2329**
	Sequential custom 2		83.05	3.05
	Face-net custom 2		84.22	0.73
	VGG-Face		81.24	1.83
Phase-III Gender Detection	Sequential custom 2	UTK_Face	**96.61**	**0.0825**
	Inception		92.76	0.89

	Face-net custom 2		93.34	0.21
Phase-IV Ethnicity Detection	Deepface	UTK_Face	79.61	0.84
	Face-net custom 2		**82.14**	**0.63**
Phase-V Height Detection	SVR	Municipality Health Centre Data	.8643	0.0819
	DecisionTree		.8974	0.0762
	RandomForest		**.8974**	**0.0762**
	Linear Regression		.6048	0.1912
	XGB		.8327	0.0846
Phase-VI Weight Detection	SVR	SOCR Heaight Weight Data	.8711	0.1001
	DecisionTree		.9121	0.0899
	RandomForest		**.9425**	**0.0861**
	Linear Regression		.6974	1.4236
	XGBClassifier		.9081	0.7891
Phase-VII Main Hydration Detection	SVR	Inhouse Data	.9342	0.0512
	DecisionTree		**.9922**	**0.0461**
	RandomForest		.9726	0.0402
	Linear Regression		.8998	0.0679
	XGBClassifier		.9818	0.0432
Activity based hydration prediction	SVR	Inhouse Data	**.9176**	**0.1068**
	DecisionTree		.8923	0.1274
	RandomForest		.8923	0.1274
	Linear Regression		.8479	0.4873
	XGBClassifier		.8842	0.1712

4.3. Comparatives study of the proposed AQUAFAZE system

To perform the comparison of the proposed AQUAFAZE system with the other traditional systems, it has been observed that no such AI enabled face image-based water prediction system is there in literature for which we are not be able to compare the performance of our AQUAFAZE system. However, there are several traditional systems that can predict the water requirement of a person by taking some user information. So, for making an unbiased comparison of ours with the existing task, we have compared the prediction of the single face image-based system with the detailed analysis system. The result of some of the sample face images are illustrated in Table 2.

5. CONCLUSION AND FUTURE WORK

The amount of daily water consumption is related to several factors like height, weight, gender, age, and level of physical activity. Even though these parameters are crucial for estimating the amount of drinking water, researchers have considered only few parameters like age, weight and height for designing water prediction system. However, due to the ignorance about these parameters, these systems are not frequently used. Considering the limitations of existing systems, the current study designed a single face image-based AI enabled water requirement prediction system, where the user only needs to turn on his/ her device camera. The proposed single face image-based system is comprising of seven different models to predict the age, gender, ethnicity, weight and height from the users' face image. For finding the most effective ML models for each task like age prediction, weight prediction etc. the performance of various models has been evaluated and the models are selected. The conclusions of the current study are listed as below:

A) Out of three ML models: DeepFace, YOLO and RetinaNet, the highest accuracy of 92.32% and loss of 0.75% was obtained with DeepFace for the face recognition task.

Table 2: Comparison of the performances of various ML algorithms in face detection, age prediction, gender prediction, ethnicity prediction, height prediction, weight prediction, and Main hydration detection

Original Images	**Detected Face Region**	**Parameters**	**Quick Analysis based Prediction**	**Actual/ Detailed Analysis based Prediction**
		Age	31	33
		Gender	Female	Female
		Ethnicity	Indian	Indian
		Weight	66	70
		Height	5'5"	5'6"
		Hydration Requirement	2.87 L	3.03 L

		Accuracy (Predicted/Actual): 94.71%		
		Age	25	24
		Gender	Male	Male
		Ethnicity	Indian	Indian
		Weight	79	86
		Height	5’7”	5’9”
		Hydration Requirement	2.57 L	2.62 L
		Accuracy (Predicted/Actual): 98.09%		
		Age	41	42
		Gender	Male	Male
		Ethnicity	Indian	Indian
		Weight	72	75
		Height	5’9”	5’10”
		Hydration Requirement	2.81 L	2.65 L
		Accuracy (Predicted/Actual): 94.31%		
		Age	22	19
		Gender	Female	Female
		Ethnicity	Indian	Indian
		Weight	59	70
		Height	5’5”	5’67”
		Hydration Requirement	1.97 L	2.02 L
		Accuracy (Predicted/Actual): 97.52%		

B) For age detection, the customized sequential model, CUSTOM1 provided the highest accuracy of 89.62% and loss of 0.2329 among all four other effective models.
C) The highest gender detection accuracy of 96.61% and loss of 0.0825 was obtained with customized sequential model, CUSTOM2. Other models like Inception and Face-net, custom2 also provided the accuracy of 92.76% and 93.34% respectively in gender detection.
D) For ethnicity detection, the highest accuracy of 82.14% and loss of 0.63 was obtained with Face-net custom 2.
E) The highest height prediction score 0.8974 and loss of 0.0762 was provided by RF. Other regressors like DT, SVR and XGB also provided the prediction score above 0.80. However, the performance of LR is very poor.
F) Like in height detection, the RF regressor also provided the highest R-squared score of 0.9425 in weight prediction.
G) Based on the predicted parameters: age, gender, ethnicity, height and weight from above models, the main hydration detection model with DT provided the highest prediction score of 0.9922 with mean absolute error 0.0861.
H) Based on the predicted basic water requirement of an individual, the activity-based hydration prediction system can predict the additional water requirement by taking the type of activity and the duration of the activity. The highest score of .9176 and loss of 0.1068 was obtained with SVR.

The study concludes that the proposed single face image-based AI enabled water requirement prediction system can be used by any user to track their daily water requirement. This will in turn help to maintain the daily water intake and thus will reduce the complicacy caused by inadequate water consumption.

List of Abbreviations
AI - Artificial Intelligence
EFSA - European Food Safety Authority
ML - Machine learning
CUSTOM1 - Customized Sequential model-1
CUSTOM2 - Customized Sequential model-2
CUSTFace_Net - customized Face-net
SVR - Support vector regressor
DT - Decision Tree
RF - Random Forest,
LR - Linear Regression
XGB - Xtreme Gradient Boosting

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Data Availability Statement
The data presented in this study are available on request from the corresponding author.

Conflicts of Interest
The authors declare that they have no conflict of interest.

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