

Blockchain-based Learning for Health Screening with Digital Anthropometry from Body Images

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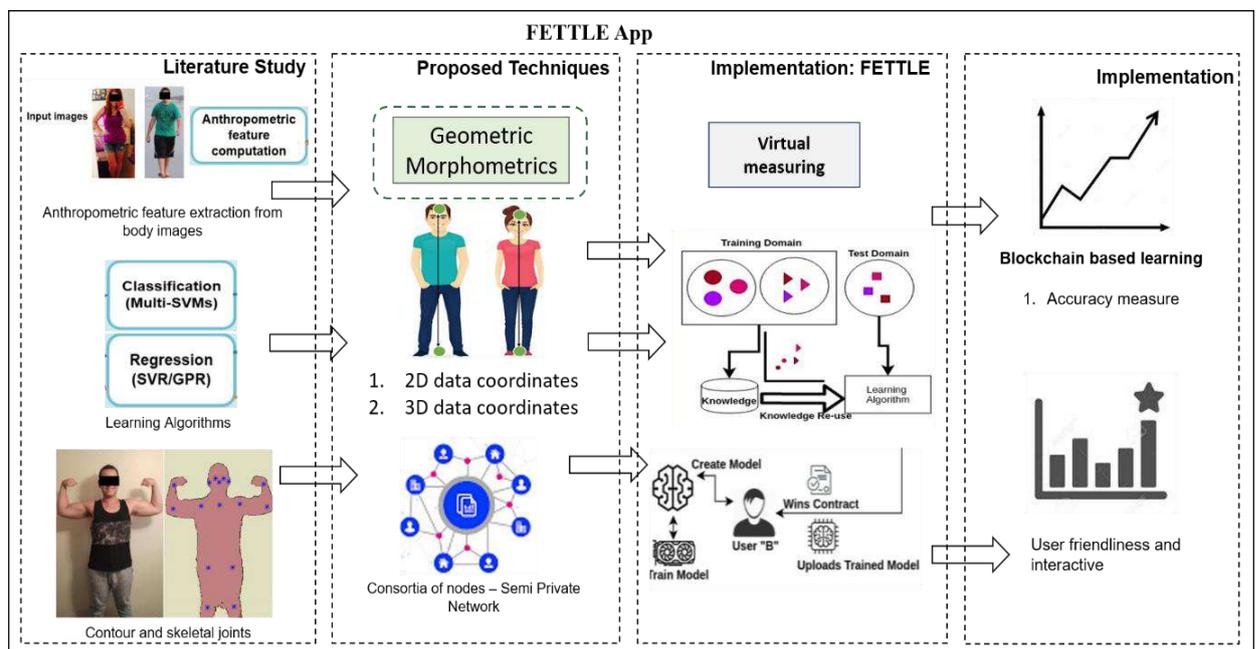
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GRAPHICAL ABSTRACT:



HIGHLIGHTS:

1. A novel imaging-based health screening in an augmented environment to quantify human anthropometric features.
2. A decentralized transfer learning mechanism for a dataset using consortium blockchain.
3. Quorum Consortium blockchain improves privacy, transactional efficiency and promotes monetization in medical data sharing.
4. The performance analysis of the framework assures that our scheme is advantageous in healthcare.

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Abstract. Anthropoid images encode reliable biometric information in abundance. Recent research on image-based screening drives this effort to investigate the feasibility of interpreting the inherent nutritional state from multidimensional human body images. However, anthropometric databases are becoming increasingly essential and grow in parallel to achieve efficient system designs. This paper presents a novel imaging-based strategy in an augmented environment to quantify the human anthropometric features with blockchain-based learning to generate a diagnosis report. It includes evaluating the attributes such as height, weight, forearm, wrist, waist, Mid-Upper Arm Circumference (MUAC), Knee, Feet, head length from an image using the Augmented Reality and Blockchain-based Transfer Learning for diagnostic accuracy. We developed a novel skeleton known as FETTLE to determine the role of body measures for assessing nutritional conditions and body weight from human body images. It forms an instantly applicable technique aimed at evaluating children's growth patterns all through their initial ages. FETTLE app can also be operated on bedridden people as a screening mechanism to spot their risk of pressure ulcers and undernutrition, followed by a more structured examination. Our approach is superior in accuracy measures with consortium blockchain-based learning context with privacy-preserved medical data sharing and high-end user experience and interaction. Our framework is proved to gain about 97.26% validation accuracy on anthropoid images.

Keywords: Stature Finder, Weight Quester, Scientific Visualization, Blockchain, Transfer learning, Augmented Reality, Digital Anthropometry.

1 Introduction

The accelerating influence of mobile gadgets and smartphones has significantly committed to the advancement of wellness screening applications. The present-day mobile and handheld devices carry high-end sensors furthermore computational strength for establishing an augmented mobile atmosphere. The usage of digital photogrammetry can be a viable alternative to the physical estimation of the human body in the medical field of research [1]. Few researchers [2] have addressed the question of information obtained by an image. A complete survey of imaging-based health screening tests is exhibited in the existing literature [3]. Usually, an image can provide implicit knowledge about the picture in terms of metric geometric relationships, as pictured in Fig.1. This technique can overcome constraints associated with the BMI calculation, precisely in the misclassification of obesity amidst the person with relatively high lean mass in bodybuilders or low lean mass in the elderly. Our approach to adopting digital images to assess human body form is predicated on evidence from earlier findings performed using either visual estimation or photographic assessment of body volume, from which body composition can be determined.

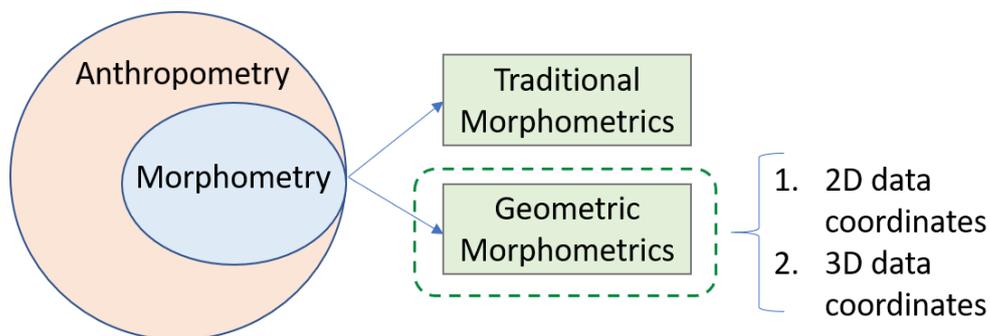


Fig. 1. Anthropometric classifications

We surveyed the FETTLE App’s remarkable scope on accurately and scientifically measuring the human body composition by determining body size, structure, and balance. Furthermore, it assists psychologists to estimate the attributes like body size, height, arm length, etcetera in correlation with other human measurements, comprising sight (e.g., color, distance, and clarity), touch (e.g., sensitivity, weight, and pain), movement (e.g., rate and reaction time), memory, and mental fatigue [4]. There are requirements on a health-related application to serve as a personal physician to monitor individual health and development in the branch of Somatometry, Cosmetology, Cephalometry, Craniometry, and Osteometry by the identification of humans. Transforming the smartphone into a personal practitioner is what the FETTLE app

is making all the way. It guides the users in knowing their health status and disease at risk by prompting their anthropometric values, thereby screening the overall wellness.

Several learning algorithms ease to infer medical information from health data. However, most machine learning algorithms are data-driven and require a training dataset from a vast number of body images and measures with heterogeneity. However, there are several real-world learning contexts where this hypothesis appears not to hold [5]. There are scenarios where the training dataset is cost-expensive or challenging to acquire. Hence, there is a necessity to design a high-performance learning model that can be trained with many easily gathered data from diverse areas. Thus, a methodology well-known as transfer learning has emerged. Its application-specific solution tends to be associated with the field of image processing and rendering. There are two stages in training a neural network of transfer learning techniques. Initially, the neural network is supplied with a voluminous benchmark dataset with generally more labels to train in the pretraining stage. Subsequently, the trained network is extensively trained with target data with comparatively fewer labels in the later stage known as fine-tuning. At the pretraining stage, the neural network is expected to be trained on the general features that can be applied to the target task to yield better performance than self-learning, where the network learns by itself. There is still considerable ambiguity concerning the impact of transfer learning on performance improvisation and the impact of the pretraining benchmark dataset, type, and size leaving open research questions for the medical image domain.

Blockchain is an emerging technology that finds its application in vast areas [6] because of its decentralized, peer-to-peer transaction and immutable nature. It is a growing data as a list of records, known as blocks, that are cryptographically linked to form chains [7]. The blocks are tied up with a cryptographic hash of the prior block, a timestamp, and transactions usually denoted as a Merkle tree. When machine learning and blockchain converge, the latter can benefit from the learning algorithm's ability to accelerate voluminous data analysis. Leveraging the two together can feasibly emerge a novel paradigm.

Inline for patients suffering from mobility issues or when the patient is too sick to stand, unconscious, or bedridden, we are in a state to depend on their subjective approximations of body height and weight rather than acquiring an actual objective measure. This paper contests the claim that bedridden patients and born children need to have their body measurements calculated while they stay in bed. Several medical research cases proved that bed confinement or difficulties in sustaining an erect and upright position, inappropriate material, lack of

knowledge, and time are well-known limitations that affect the systematic body measurements in hospitalized patients.

The remainder of this paper is structured as follows: section 2 elaborates on the research works related to our problem statement, followed by section 3 that provides a system overview. High-level Architecture is detailed in section 4. The fifth chapter is concerned with the methodology used for this study. Observed effects are presented in section 6, whereas Accuracy and performance analysis in sections 7 & 8. Finally, the conclusion gives a summary and critique of the findings paving the way to the identification of areas for further research.

2 Related Work

The human attributes quantification procedure from an image in a two-dimensional illustration is described in previous researches [8]. The human body fat calculation method is beneficial in generating the dataset for weight prediction [9]. It projects a computational core to process both single two-dimensional images or a pair of 2D models to examine body weight and BMI. This work elicits five anthropometric traits for bodyweight analysis that incorporates ratio between waist width to thigh width, waist width to hip width, waist width to head diameter, hip-width to head diameter, and body area between waist and hip. Notable body point labeling and tracking introduced in [10] is valuable for predominantly marking the body point. The discussions made in [11][12] have put forward a distinct dimension of 3D reconstruction concerning human body shape from a single-line depth camera. Several authors [13][14] have attempted to employ graph-cut algorithms for shape segmentation, but currently, there is still no widely accepted methodology to sectionalize.

A real-time approach to incremental scene perception with mobile platforms reveals how AR is rendered in the camera scene [15]. ARKit is capable of detecting a maximum of 100 images simultaneously to automatically estimate the physical size of the object in the captured image. It is capable of generating three-dimensional mesh data from the screen geometry [16]. The method of deducing standing human bodies from single images using the calibration models is presented in the previous works [17]. The purpose of the researcher's inquiry in [18] was to develop and validate a computer algorithm to offer a precise estimate of the percentage of body fat practicing digital photographs. The research on computer vision-based human body segmentation and posture estimate explains the human body segmentation of varied postures and estimates the segmentation results [19]. Another approach on age synthesis and estimation

via facial images describes human face recognition concerning age and other factors [20]. The literature [21] tends to use a methodology to refer to 3D facial landmark localization with regression from extracted features. It details the landmark localization of the human body shape triggering it with an asymmetric design, thereby applying shape regression. The other strategy uses kinects in scanning 3D full human body images to perform the full-body scan and extract the features as required [22]. Typical study on privacy-preserving cloth trial with Mobile Augmented Reality aids in bringing out the cloth try-on mode of picture rendering to size attribute [23] [25]. The method for extracting facial characteristics by 3D facial landmark localization [24] by asymmetric patterns [27] and shape regression [26] from deficient local features has been proposed [28]. Experts have always seen 3D imaging as a rich source of age estimation and synthesis [30] [33]. Motivated by the research works [31][32], blockchain can share data and learning models in a deep learning framework to enhance transfer learning in a decentralized and distributed environment. With the help of learning strategies to govern blockchain, there is also a chance to enhance security significantly.

Further, as learning algorithms love to work with many data, it creates an opportunity to build better models by taking the benefits of blockchains' decentralized nature that encourages data exchanges. Health apps [29] [34] typically aid two types of functions. The primary task is to collect or store health-related records, which some applications enable the user to share with a health care provider. Another task is access to health information, such as nutrition data on balanced foods, healthy diets, and workout routines. However, exclusive early efforts required vital labor to process the images and figure out the body mass. Using automated digital image analysis, the computerized visualization method might overcome some of the problems and the visual estimate of body volume and consistency. Therefore, this research aims to promote an easily accessible, compact, agile, and comparatively economical but efficient computerized image interpretation with the blockchain-oriented learning process for large-scale estimation of nutritional deficiency in its more initial stage.

TABLE 1 Qualitative comparison of literature with related work.

Factors	[3]	[9]	[25]
Image-based screening	✓	✓	✓

Anthropometric features	X	Width of waist, thigh, head, hip, and body area between the waist and hip	X
Data source	Scan images (Ultrasound, MRI, CT)	Human body images from cameras (2D front view)	Full-body images: Front, back, and side view
Learning strategy	X	X	✓
Screening	Cellular carcinoma and Cancer	Bodyweight analysis	Body mass and fat

Novel Contributions

A blend of Augmented Reality (AR) and Deep Learning is explored to be a striving feature of the FETTLE App solution. Our proposed methodology uses AR technology to scientifically determine human characteristics and train the app to estimate an individual's health risks. By gaining the Mobile App camera with image rendering to screen, human health is a thriving feature of FETTLE. The predominant work of this solution is analyzing the anthropometric results of a person by matching the current health trends. Detecting the health risks from a single image captured by a mobile camera by triaging the anthropometric information is the highlight of this novel approach. FETTLE analytically relates the training set of health reports with the captured image of an individual to ensure experimental extinction, similar to a medical practitioner in fixing the health risks. It renders a privacy-preserved and trusted technique of sharing data with peers among consortium blockchain networks in the learning domain and permits an innovative prospect of incentivizing smart contracts. Table 2 lists the notations and symbols used throughout the manuscript.

TABLE 2 Notations and symbols used

NOTATIONS AND SYMBOLS	DEFINITIONS
AR	Augmented Reality environment
BMI	Body Mass Index
BMR	Basal Metabolic Rate

ResNet	Residual Networks
CNN / ConvNet	Convolutional Neural Network
ω	BMR value
λ	Height
δ	Weight
γ	Age
F_λ	Height of the Father
M_λ	Height of the Mother
β	Knee height

3 FETTLE: System Overview

In general, ARKit is the framework that renders scene-capturing features for image processing and transcription. FETTLE is an ARKit application that enables the back and front camera of the device to image the detected special points by locating any number of 3D objects in space. It performs vector operations to calculate the distance and direction of the camera from a point in imaging space to assess the volume of the object despite the movement of the camera holder. This data is later used to generate the control points. Further, the application quantifies the distance between the special points and holds back the statistical information about the special points in a detected plane to a file to generate a 2D or 3D content. A significant feature of this app is model creation that facilitates the construction of a visual object for the effectual constitution of 3D data. The generation of a 3D model from 2D or 3D health images integrates in real-time to turn it to be more interactive and effective application.

The human body images are captured from a mobile camera or smartphone in an augmented context. It needs to be pre-processed by cropping the detected shape from the original image to fix the control points. The coordinates of control points are used for the extraction and computation of anthropometric measures. We employ the Convolutional Neural Networks (CNN) scheme for detecting body images. By implementing the CNN scheme onto the image, the body sections are marked out as a region of interest, while all other areas of the picture are specified as the background and dropped out. A piece of comprehensive knowledge about human body proportions is used to initially calculate body parts that accompany the virtual measuring to derive the anthropometric characteristics and computation. If the training and validation data are procured from digital camera viewpoints, conventional machine learning

procedures can predict results better. However, when the training data is of digital camera views, and the validation data is from anthropometric characteristics, then the prediction effects are apparent to deteriorate due to the data variance in the domain. An alternative means to inspect the data domains in a transfer learning context is that the training data and the validation data are diverse sub-domains connected by a common high-level area. Hence, we need transfer learning, as there is a confined quantity of target training data. The detailed system overview is described in the subsequent subsections, which covers the entire concept of delivering a valuable app for estimating an individual's health screening. The system insights are diagrammatically presented in Fig. 2.

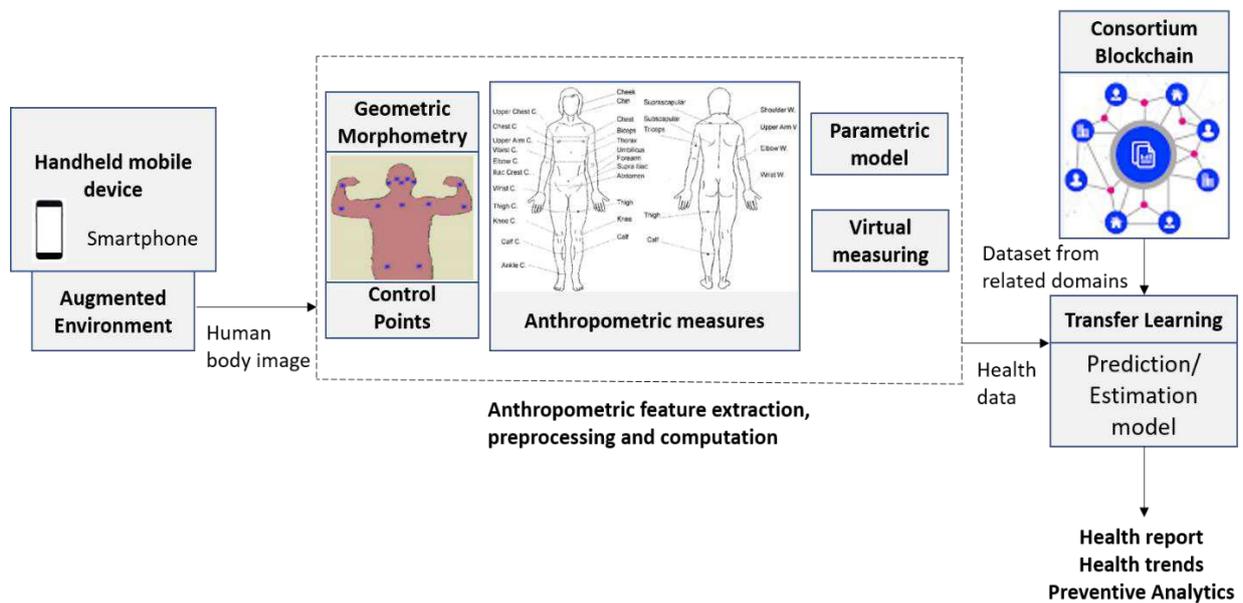


Fig. 2. FETTL: System insights

3.1 Adulthood Space

The Adulthood Sector of the app furnishes the digital anthropometry of an adult to screen their health risk and analysis, if any. A diagnostic health screening from a human body image with virtual measures is one of the novelties of our approach.

The stature Discoverer section initiates the camera to capture the photo of a person subjected to the AR Scene to determine the height. It further instructs the users on their position to capture a quality image worth measuring an accurate height by standing barefooted on a hard, flat surface with back alongside a vertical plane and feet be set apart just less than shoulder-width. By setting up the control points on the image, as shown in Fig.3, the app shares the information left to the user to manipulate how to place the control points for a height discovery.



Fig. 3. Setting up of control points for height tracking

Weight Quester module takes the captured photo with 3D coordinates as input in both the front view and a side view to compute the abdominal circumference to conclude the user's weight from the image captured in the camera scene. A reference picture is also displayed to train the user in placing the control points in the captured image.

Fitness Calculators

Following are the fitness calculator sections to define the fitness status of a person in terms of Body Metabolism values.

Body Mass Index (BMI) is calculated from the extracted anthropometric values such as height, weight, and gender attributes captured from the body images. The category of the individual based on their BMI value is delivered. The following formula determines the obese, regular, and underweight status based on the BMI value.

Basal Metabolic Rate (BMR) is calculated from the attributes like weight, height, and age. The below equation details the computation of the BMR of an individual. Typically, BMR denotes the number of calories the body burns at rest to retain healthy body functions.

$$\omega = (10 * \delta) + (6.25 * \lambda) - (5 * \gamma) + 5 \quad (1)$$

where, ω = BMR value, δ = weight, λ = height and γ = age

The athlete Space module is useful for an individual in terms of the athlete world. The fitness report in playing is the motto of this module. FETTLE helps athletes to monitor their Fitness status by the anthropometric values obtained from their image.

3.2 Baby Care Space

The Baby Care Space is developed to determine the baby's anthropometry from an image. This section acts as a Baby Nutritionist in assessing the Baby growth and deficiencies.

Baby Nutritionist space determines the health status of the baby in terms of nutrition and growth. This section receives the image of a baby from the user and studies the image by analyzing it. Here presented a Convolution Neural Network model to determine the disease of the baby from an image. The CNN model created is triage the picture obtained from the user to compare with the dataset fed into it containing the Malnutrition diseases like Rickets, Marasmus, Kwashiorkor. The FETTLE app not only returns the name of the disease; instead, it determines the probability of the disease in the image.

Ideal Baby Weight This section calculates the ideal weight of the baby throughout various stages of its growth. This calculator computes the weight of babies from their birth up to seven years. The below-derived formula is throwing the right results for both Male and Female babies wherein the γ determines the baby's age, and δ determines the ideal weight of the baby.

$$\delta = 9.5 + (2 * (\gamma - 1)) \quad (2)$$

Baby Height Predictor Usually, the child's height is based on parental heights subject to regression for the mean. It indicates that very tall or short parents are liable to have a taller or shorter child than regular; however, they are probably nearer to the average height than their parents. Here F_λ is the Father's height, and M_λ is the Mother's height used in the below formula, which predicts the baby's future height, which is λ .

$$\lambda = ((F_\lambda + M_\lambda) + 13)/2 \quad (3)$$

Baby Milestone Calculator This section determines the child's development to assess the baby's growth and helps to track the developmental landmarks of the baby as it becomes older. Results from this section are helpful to identify whether the baby is developing typically or not.

4 Immobilized Patients Anthropometry

This module is specially developed for bedridden patients to determine their anthropometry.

Bedridden patients wing In this section, hospitalized patients were subjected to anthropometry, which is easier to monitor regularly. Measurement of height within the critical care unit is essential for approximating ideal body weight. FETTLE provides a solution in

estimating the height and weight of bedridden patients. Yet another possibility is to identify the spread, and severity to diagnose the stages of pressure ulcers (bedsores) from digital images.

Height determination In this ideality, our novel approach is to obtain the height of the bedridden patients from an image using the below formula where λ is the height of the patient, β is the knee height of the patient, and γ is the age of the patient.

$$\text{For men, } \lambda = [1.94 * \beta] - [0.14 * \gamma] + 78.31 \quad (4)$$

$$\text{For women, } \lambda = [1.85 * \beta] - [0.21 * \gamma] + 82.21 \quad (5)$$

Knee height measurement is also symbolized the below Fig. 4

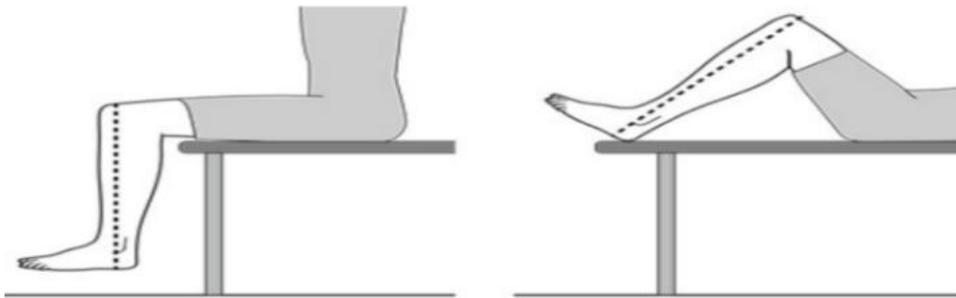


Fig. 4. Knee Height measurement from critically ill patients

Bedsore severity assessment This section allows to capture the digital image of the skin affected area to set the sights on image analysis. The stages and severity of the pressure ulcers can be inferred. This module mainly depends on the peer data obtained from the blockchain module.

4.1 Health Trends

This section exclusively assists the app users to keep hold of a health record to track their health status based on the overall anthropometric results acquired with the current health trends. A comprehensive report of an individual user is provided with visual trends. We have employed an exclusive blockchain network that aids in learning by extending the medical data/dataset privately shared.

5 High-Level Implementation Architecture

A high-level system architecture diagram is detailed in the below Fig.5 User log in to the app; new user registration is also available; thereby, the user gains access to the FETTLE App. Once login is the successful user enters a health screening section. The user interfaces consent in drawing out the data from the virtual environment in proportion to the availability and accessibility of the objects. The augmented world has options for arriving at the report as well as comparing it with the trends. We use the coordinates of the detected and manipulated control points for the computation of anthropometric features. All the submitted measurements are automatically corrected for the entry of decimal units.

Similarly, the measurement entries are also fixed for their length. If the decimal figure positions recorded for a dimension exceeds the allowed figure of places for that particular dimension, the user is prompted. The cursor does not progress until the issues are resolved. The user's values fall beyond the specified marginal values for body measurements, and the user is flagged for short verification. Besides the advanced imaging techniques, morphometrics are concerned for their quantitative methodologies to seek information regarding variants and changes in the bodily structure that portrayed the association between the human body and diseases. The geometrical morphometric measurements employed in the medicinal field remain extensively used in the diagnosis and the follow-up. The user has the preference to stock their data in the cloud storage allotted for the user. We preferred cloud storage rather than blockchain storage to avoid retrieval time and cost.

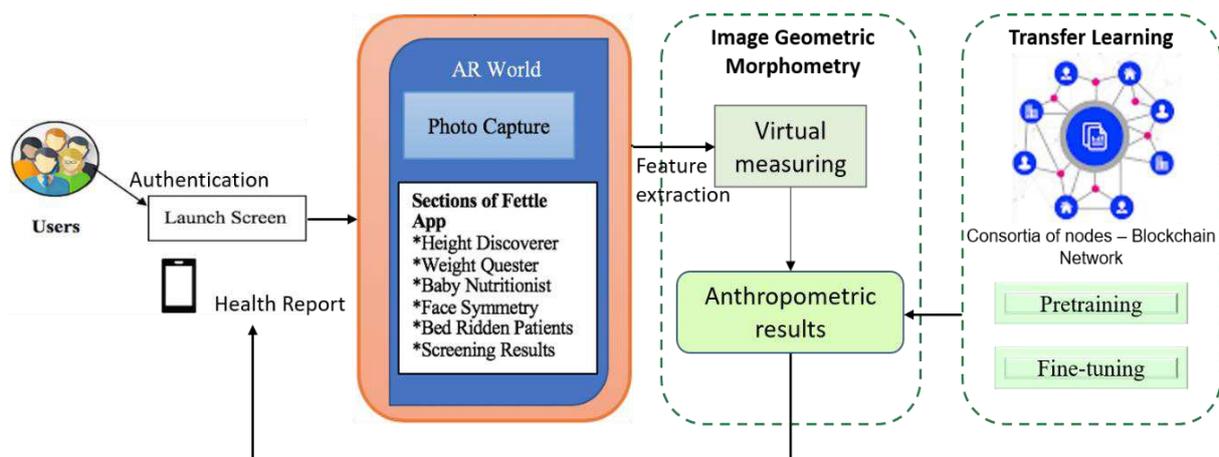


Fig. 5. FETTLE App Architectural blocks

6 Methodology

Anthropometric information from a human body in terms of circumference, skinfold, and width is acquired. The detailed novel approach shown in Algorithm 1 applies the transfer learning methodology to learn the anthropometric values obtained from an image. The images are resized to a dimension of 299×299 in default to be able to process by ResNet.

TABLE 2 Technologies used

Technology	Descriptions
Augmented Reality	It overlays a computer fabricated image on a user's interpretation of the real world to render a complex view
Geometric Morphometry	The biological shape is outlined by transforming the original form as a reference shape, and the data represents the geometry of the structure being studied
Deep Learning	It enables the system to learn without human interference, dragging from the former validated cluster of data
Transfer Learning	Learning strategy that emphasizes the storage of knowledge obtained through solving a problem of a different but correlated problem
Consortium Blockchain	Semi-private blockchain network with a controlled set of nodes making a highly trusted environment to enable privacy preserved data sharing

Feature Extraction

The features to be extracted are the anthropometric measures from the real-world human body images. Owing to the limited number of training data, the employed classifier evaluates deep transfer learning for feature extraction via three deep pre-trained CNN architectures of Residual Networks.

The setting of the learning environment: The contemporary three layers of pre-trained models are customized to adapt the network for intended classification. The modifications are to be performed only to the layers of the classification stage holding back the knowledge gained. The fully connected (FC) layers in the pre-trained architectures are superseded by FC layers that characterize the three kinds of malnutrition. Conclusively, the fine-tuned pre-trained models are used for learning with anthropoid image data. The last three FC output layers carry out the classification tasks with Rickets, Marasmus, and Kwashiorkor classes rather than the default

1000 classes as originally designed for the ImageNet dataset from which the weights are loaded.

Convolution: For 3D images (height, weight, depth) filter of the convolution process is also in 3D; hence Multiple feature maps are generated.

Pooling: In our 3D image data sets, pooling keeps depth, reduces height and width by preserving valuable information. It also reduces overall network training time. Fine-tuning not only retrains the classifier stage but also the convolution and pooling layers of the feature extraction stage.

Classification: The previous layer's output is directed to a Fully Connected FC layer, which produces an N-dimensional vector. Each number in the N-D vector becomes the probability of a class. Class with the highest probability is chosen for predicting the diseases.

Applying Transfer Learning: The pre-trained CNNs are residual learning-based variant structures of residual networks. The chosen layer structure includes ResNet-18, ResNet-50, ResNet-101 architectures that simplify the training of the deeper networks and cut down the errors from increasing depth. The residual block assumes a special significance because it allows the network to escalate in-depth without gradient degradation. We use it as an initial point in our problem, as shown below in Fig 6. The model works well because the initial layers of the ResNet model have already learned features used commonly.

Training Parameters: We train the networks by stochastic gradient descent with the momentum of hyperparameter value to be 0.99 for transfer learning by using the default Rectified Linear Unit (ReLU) activation function. A differential learning rate of 10^{-6} for the lowermost layers, 10^{-4} for mid transfer layers and 10^{-2} for the new three, fully connected layers have been imposed. The batch size is maintained to be 256 images. To speed up the learning in the new layers, we rise the weight learn rate factor and the bias learn rate factor to 10. The networks are validated every 10 epochs during training.

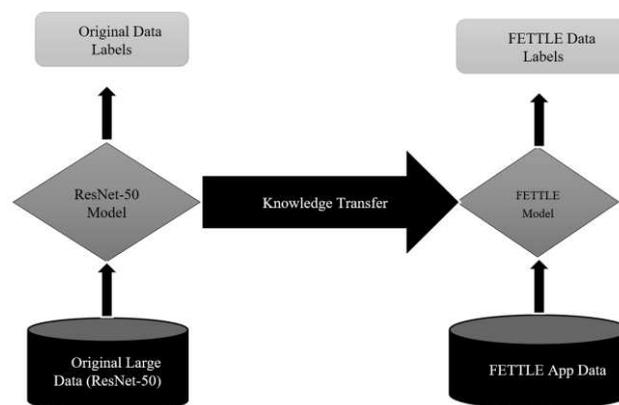


Fig. 6. Transfer Learning of FETTLE App Model

FETTLE App dataset is different and not analogous to the existent dataset on hand, so we retrain our entire ConvNet from scratch, as shown in Fig 7. We consider the input to our new fully connected layer as Bottleneck Feature.

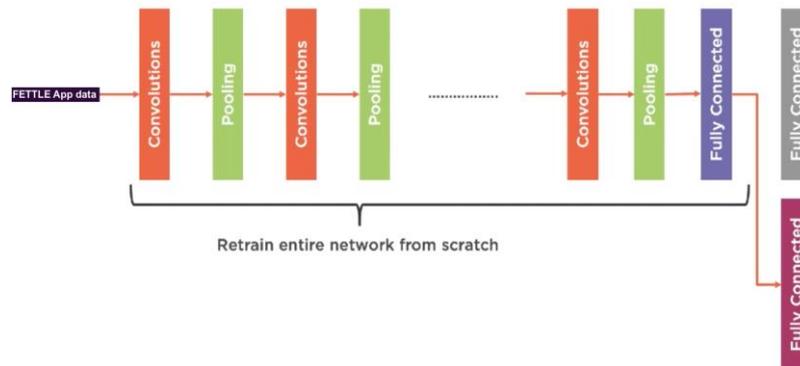


Fig. 7. CNN Model Training of FETTLE

Algorithm 1: Health screening from image

Input: Image captured from camera or picked from Photo Library.

Output: Anthropometric values, along with health screening results.

Procedure Capture (camera scene view)

1. Scene graph \leftarrow Organize the scenes in a tree-like structure
 Root node: It defines the coordinate scene system
 Nodes: It represents the position in a scene that can attach elements to such as lightning or geometries, which are visible elements.
2. Encapsulate (real-world location)
3. **for** each node in a scene, do
4. Check for transformation matrix relative to the root node
5. Transformation matrix \leftarrow Position, Rotation, and Scale (node)
6. Observe the Physics Body in the camera scene
7. Implement the action
8. Apply transfer learning methodology to determine accurate results.

Procedure Encapsulate (real-world location)

1. Determine the center point of the camera from the scene viewpoint
 2. Camera location \leftarrow [cameraTransform.m41, cameraTransform.m42 and cameraTransform.m43]
-

-
3. Camera orientation ← component values from the Transform matrix

Procedure Acquire_Data (camera scene)

1. Transform Matrix: A rectangular array of numbers
2. Store Camera location and Camera Orientation in Transform Matrix
3. Scene Vector: New three-component vector created from individual component values

Procedure Observe (Physics Body)

1. Concern six degrees of freedom (6DOF) to track the object
2. Done hit testing to ensure the other exciting features that were caught on the track
3. Analyze detected feature points to determine the required object in the scene

Dataset acquisition: Transfer learning renders a chance for the model to be trained and applied to specific data domains and predict in various areas of future data. However, predictive and preventive analytics are more efficient when the process involves a rich set of data. The health and malnutrition variables from the health, nutrition, and population statistics dataset of the World Bank[35] from the year 2015 are transposed to have 8,730 sample images. The complete dataset with indicators was made publicly available by the World Bank. Further, we also run an exclusive blockchain module to acquire real-time datasets from the volunteer providers to prepare a transposed subset. This module helps the transfer learning process to be more efficient.

Blockchain-based learning: A consortium blockchain-based trusted environment is set up to facilitate medical data sharing among the data holders. A Quorum network is deployed among the registered users who want to share their health data. The users are permissioned to enter the network only if they accept the terms and conditions of sharing their data/dataset to the peers to ensure privacy. The validators are the set of data scientists and administrators who are the verified stakeholders of the system, and the validators are dynamically nominated after several rounds. With this confined network, the transparency of data can be restricted to the provider and requestor. Quorum uses Tessara for encryption while sharing the data among the nodes. Quorum, by default, has free gas and does not entertain economic incentives. However, we write smart contracts on top of the blockchain module to implement a monetization system to encourage the dataset providers. To ensure the interest of blockchain participants involved in transfer learning for deep learning, we provided an incentive mechanism.

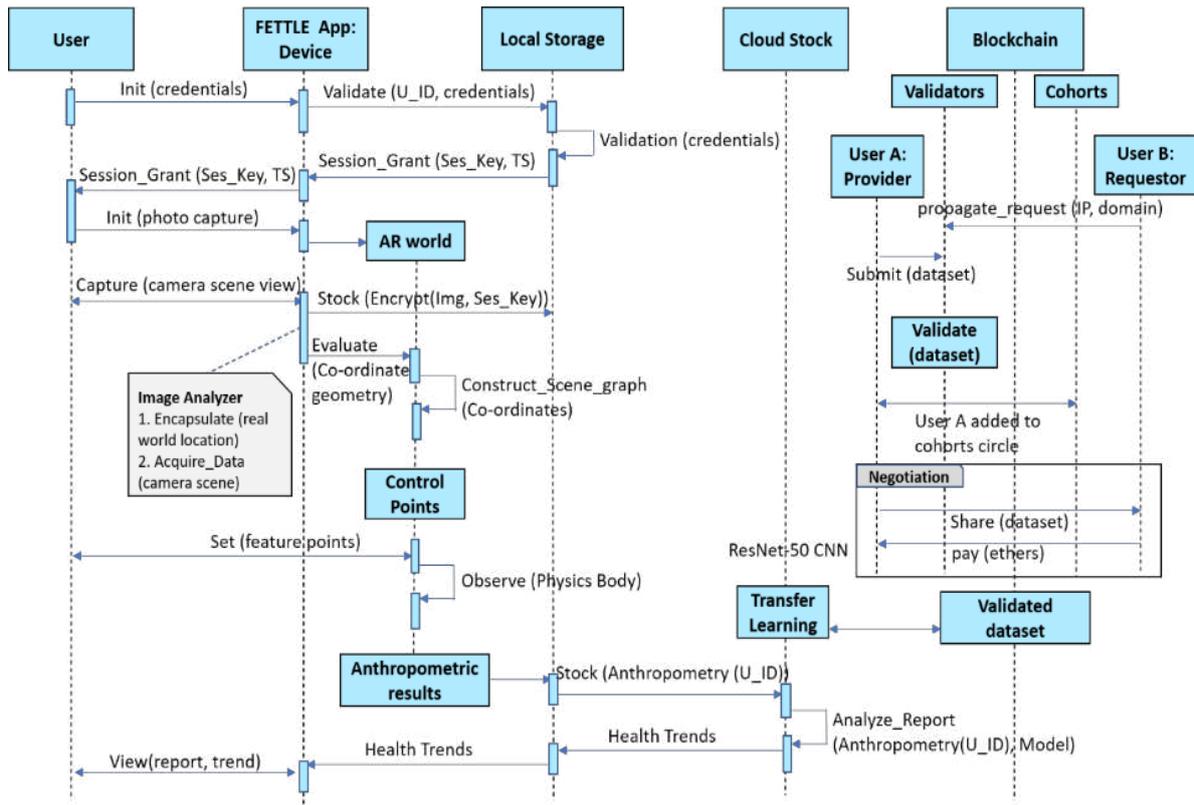


Fig. 8. Sequential workflow of proposed FETTLE

The incentivization uses ethers as cryptocurrency by leveraging the underlying Ethereum base, used in data sharing from one user to another to respond to service or resource utilization. If a user has a large dataset and can be given medical diagnostics, the user can automatically rent that dataset for monetary benefits by sharing it using a private channel. However, the pseudonymity is preserved as it is private data, and the scheme is elaborated in Algorithm 2. The provider can ask for a certain amount of ethers for data exchange to use the dataset by some other users. The overall sequence of actions that can be performed with the system is depicted in Fig 8.

Algorithm 2: Incentivized data sharing for Transfer Learning

Input: Medical data/dataset of a user.

Method: Sharing of data with peers for monetization.

Output: Dataset for transfer learning for another user.

Peer nodes = {set of validators and cohorts}

NODE	DESIGNATION
------	-------------

Validators	Full and mining node
-------------------	----------------------

Cohorts Lightweight node

Validators = {set of data scientists and administrators}

Cohorts = {System users those who agreed to share their medical data/dataset}

Procedure Data_Provision (User U_A)

1. **for** each user, U_A agreed to share its medical data/dataset
2. Granted permission to participate in consortium blockchain
3. U_A is added to the cohorts set
4. U_A submit its data/dataset to the group of validators
5. Validators run **validate(data/dataset)** on the submitted data/dataset
6. **if** data/dataset is validated, **then**
7. Validators mine it to a block/new block
8. Append the block to the end of the chain

Procedure Validate (data/dataset)

1. Check for the domain of the medical data/dataset
2. Cluster \leftarrow Store and accumulate data on solving a set of problems (domain)
3. Check for its application to another set of similar problems (sub-domains)

Procedure Data_Requisition (User U_B)

1. **for** each user U_B requests for a medical data/dataset
2. Propagate the request (requestor_IP, domain of data)
3. **if** User U_A agrees to respond to the request, **then**
4. U_A notifies the validators to communicate with U_B
5. Validators facilitate $U_A - U_B$ data sharing in the access control layer

Procedure Share and Incentivize (User U_A)

1. User U_A executes the smart contract to reach U_B
 2. U_A asks for 'n' ethers in exchange for n data usage of the dataset
 3. **if** U_B agrees on the demand of U_A , **then**
 4. U_B uses the data/dataset of U_A and transfers the ethers by inducing its smart contract
 5. Cluster \leftarrow U_B stores this data/dataset in its local storage and uses it for learning to solve problems from similar domains or its sub-domains.
-

Mathematical Model

We consider a source domain space \mathcal{D}_S and target domain space \mathcal{D}_T represented by twin tuple with instance space (Z) and hypothesis space (w) enclosed. The objective function can be defined as the marginal probability between the label space (\mathcal{L}) and the hypothesis space and is denoted as η .

$$\mathcal{D}_S = \{Z, w = P(Z)\}$$

$$\eta = P(\mathcal{L} | w)$$

The source and target constraints differ in three feasible ways in our case.

1. The instance spaces of source and target domains are distinct. Z_S and Z_T
2. Domain Adaptation Technique: The marginal probability distribution of source and target domains are distinct. $P(Z_S) \neq P(Z_T)$
3. There is adrift in the conditional probability distribution of source and target domains are distinct.

$$P(\mathcal{L}_S | w_S) \neq P(\mathcal{L}_T | w_T)$$

The transfer learning is a mapping function that randomly maps training data $z \in Z$ to a hypothesis $\mu \in w$ defined by a conditional distribution, $P(\mathcal{L}_T | w_T)$ with the information gained from the source domain space in consort with the blockchain collected peer medical data (\mathcal{B}_d) implied by Info-Gain ($\mathcal{D}_S + \mathcal{B}_d$).

Table 1. Tech Stack Version details.

Technical Details	Version
Programming Language	Objective C 2.0, Swift 5.0, Python 3.7.4
Framework	Core ML 3.0, ARKIT 3.0, Turi Create, Keras 2.3.0
Platform	iOS 13.1
XCode	10.1
Mac OS X	10.14.6
Blockchain framework	Quorum
Enabled consensus	RAFT
Smart contracts	Solidity 0.4.25

7 Experimental Results

The development environment is set up as per the technical details listed in Table 1. The image captured from the AR environment is subjected to experiments with varying anthropometric results, as detailed in Fig 8. A comparison of actual anthropometric values with the digital anthropometric results obtained gives an accuracy of 97.26%. Baby MalNutrition Detector studies the images using an image classifier customized to predict the MalNutrition diseases. Python code is used to train the CNN model named “FETTLE MalNutrition.h5” using the disorders of MalNutrition in the form of images. The obtained “FETTLE MalNutrition.h5” is then converted to “FETTLE MalNutrition.ml model” to use it in the iOS CoreML code, which accurately predicts the result on a single click of the button in iPad/iPhone devices as in Fig.9, which describes the result from Turi create visualization. Our model experiment detects the MalNutrition diseases such as Rickets, Marasmus, and Kwashiorkor with reasonable accuracy. Hence our testing implies that this approach can also detect other undernutrition baby diseases. Table 2 depicts the performance of the sharing process supplied by the blockchain module to the framework.

Table 2. Performance analysis of the blockchain module.

EXECUTION ON CONSORTIUM BLOCKCHAIN	TIME COMPLEXITY (in milliseconds)
Smart contract creation	18045
Smart contract update	2039
Raft block time	50
Transaction processing time	2028

Turi Create Visualization			
	path	image	DiseaseType
2	/Users/malini/Roselin_WorkSpac...		Kwashiorkor
3	/Users/malini/Roselin_WorkSpac...		Kwashiorkor
4	/Users/malini/Roselin_WorkSpac...		Kwashiorkor
5	/Users/malini/Roselin_WorkSpac...		Kwashiorkor
6	/Users/malini/Roselin_WorkSpac...		Marasmus
7	/Users/malini/Roselin_WorkSpac...		Marasmus
8	/Users/malini/Roselin_WorkSpac...		Marasmus
9	/Users/malini/Roselin_WorkSpac...		Marasmus
10	/Users/malini/Roselin_WorkSpac...		Marasmus
11	/Users/malini/Roselin_WorkSpac...		Rickets

Row # 13 rows

Fig. 9. The output of Turi Create Visualization

8 Performance Analysis

Our model improves its accuracy by employing the following constraints.

- Applying Transfer Learning
- Procuring additional data for training
- Using a more complex, deeper (more layers) CNN

It is apparent in the chart below (Fig 10) that the FETTLE app, when made to learn by self with data and deep learning architecture, achieved a relatively lower accuracy when the transfer learning module is done to equipped so that the model learned from the experience of others with higher accuracy.

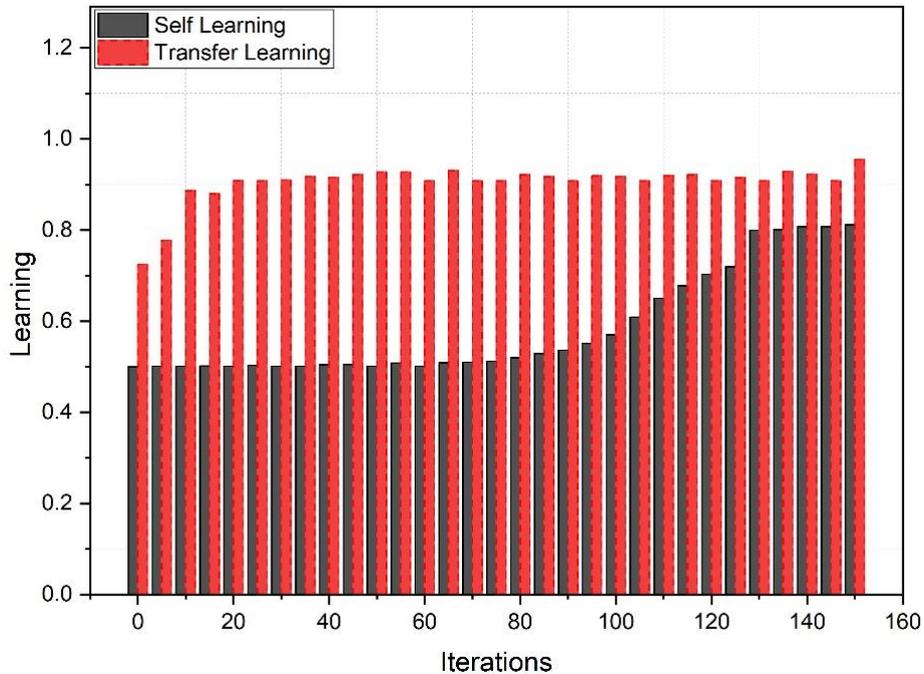


Fig. 10. Analysis on model accuracy amid self and transfer learning

The train data are used to train the model, which can be used on the test data to validate the fitting of hyperparameters to the model. The hyperparameters on the number of nodes per layer are adjusted on each run. The reduction of the number of nodes composes the learning of the model to be slightly tricky. A random dropout of neurons has been deployed to regularize the neural network to cut down the neurons' dependency to decrease overfitting. A tabular summarization of our model's accuracy with validation data over training epochs of 10, 20, 50, 90 iterations are depicted in Table 3, and Table 4 shows the R-squared value of the models.

Table 3. Model accuracy.

CNN Architectures	Iterations			
	10	20	50	90
ResNet-18	96.72	96.98	97.83	97.87
ResNet-50	97.17	97.22	97.26	97.19

ResNet-101	95.99	96.18	96.62	96.43
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Table 4. The R-squared value was obtained on the models.

Models	R^2 values
ResNet-18	0.926
ResNet-50	0.971
ResNet-101	0.908

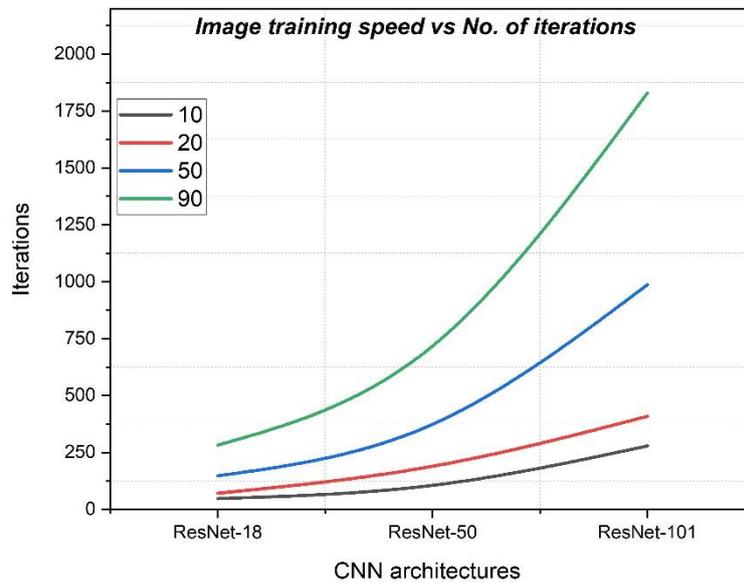


Fig. 11. Image training speed on various epochs

Fig. 11 reveals that there has been a strong relationship between the speed of the training increases gradually with incremental iterations, which infers on less time consumption for less number of iterations. However, the model accuracy is neither induced by the iterations, nor the CNN architectures. The correlation between the model accuracy and the image training speed can be assessed with our pre-trained networks on different epochs respectively are revealed in the graphical plot of Fig.12.

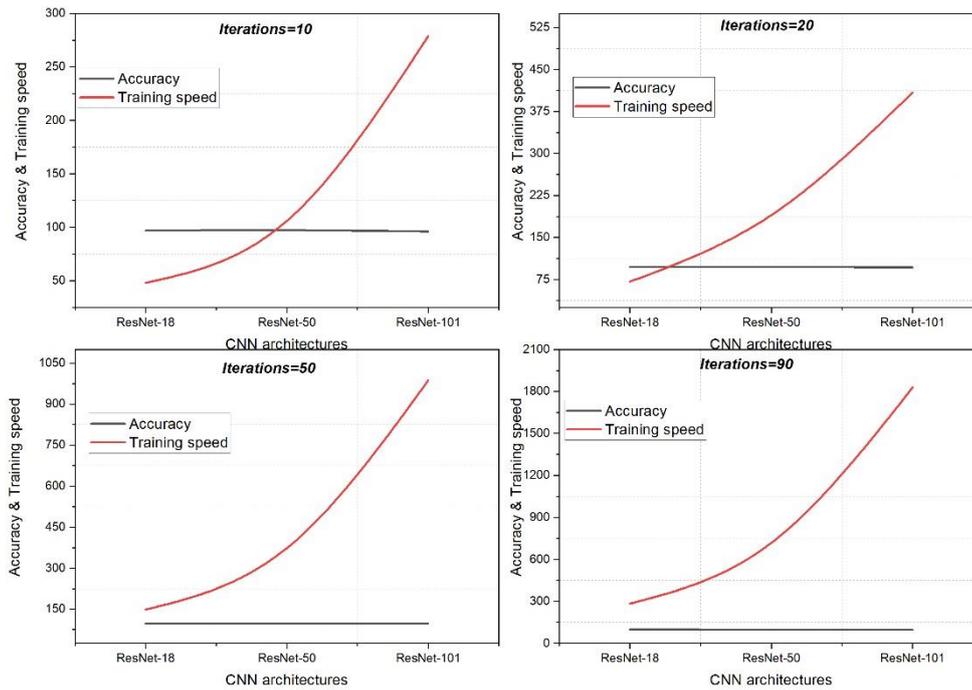


Fig. 12. Accuracy of Baby MalNutrition Detector on various epochs

Sensitivity measures how likely the model misguided a person on his/her health status, whereas specificity points to the measure on the model that correctly diagnoses a person with their fitness level. It is evident from Fig 13 the blockchain-based transfer learning outperforms transfer learning in terms of sensitivity and specificity.

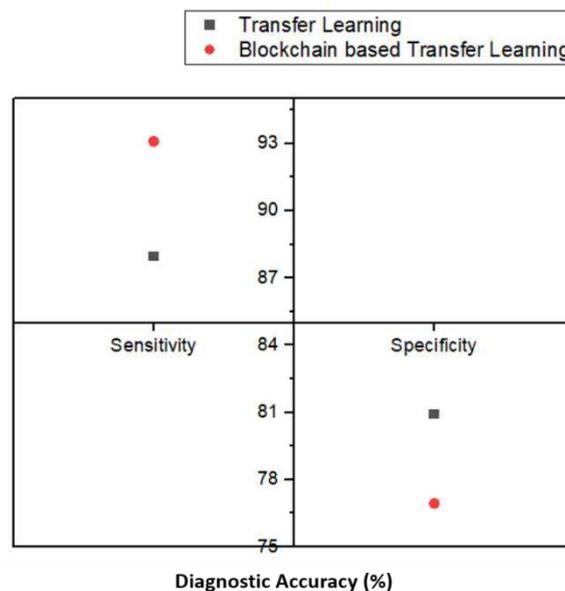


Fig. 13. Sensitivity and specificity on the model

The usage of indoor scene understanding in our novel approach is efficient in memory and computational time.

Model Performance:

- Gradient Descent Algorithm is used for optimization by minimizing function iteratively with the help of Backpropagation in our CNN.
- Image Augmentation and Hyper-Parameter Tuning methods are employed to yield better performance of our model.
- Image pre-processing technique like rescaling is followed to ensure that the training images are appropriate for accuracy.
- Usage of Turi Create produces a reasonable model size, optimized, and specialized for iOS Mobile environment.

Table 5 lists the factors by which we determine the overall performance of our FETTLE App.

Table 5. Performance analysis of FETTLE.

Metrics	Performance yield
Numerical Calculations	The test measured the time to calculate the number n to ten thousand decimal places, for which our app is returning a better result.
Network Support	This test measures the reachability of the network in both the online and offline modes of the app. FETTLE yield a good result even in this experiment.
Image Training Speed	Training speed is an important test to be carried out since many of our modules are handled with images. Since we have used ResNet CNN as an image classifier, the overall app size is pretty good compared to other classifiers.
Computational power	FETTLE App yields a good result in computational power since it uses most of the iOS Native plugins and Frameworks. The use of ARKIT and COREML is one such example to obtain better performance.

Abbreviations and Acronyms: FETTLE App define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract.

9 Concluding Remarks

This work examines the relationship between human body composition and visual body appearance to measure health from multidimensional body pictures. We presented a deep convolution neural network as a transfer learning methodology for identifying human anthropometry scientifically. We proposed a module that provides a decentralized blockchain-oriented learning strategy. The primary motivation behind FETTLE App was the need to design an efficient algorithm for determining anthropometry to assess health screening with the aid of mobile cameras. A digital health guide strives for each of us to identify the health risks proactively before seeking a medical practitioner. Our approach is guaranteed to render a health estimate from body images visually based on all investigational outcomes. As the future scope of the work, we are trying to share the training model among the peers and to lend a dataset on a timely basis. Forensic anthropometry can be developed for detecting criminals by comparing the fed criminal photographs into FETTLE.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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