International Research Journal of Multidisciplinary Sciences **ISSN:Awaited**
Volume 1 Issue 1 Month jan 2025 PP 1-18

AnthropometricParametersMeasurement Methods: a geographical review

KavitaKumari[*]andDr.YazdaniHasan[**]
[*]HIMTGreaterNoida,UP, India

[**]NoidaInternationalUniversity,GreaterNoida,UP,India

***Abstract*—For basic health surveillance, we have anthropometric metrics. Anthropometry is a branch of morphometrytostudiesthesizeandshapeofthecomponents ofbiologicalformsandtheirvariationsinpopulations.Inthis paperanationalgeographicalreviewisdonefordetectingthe nutritionstatusamongchildren.Also,thestudydescribesthe variousMLtechniquesappliedfordetectingnutritionalstate using anthropometric parameters.**

I. INTRODUCTION

Health analysis has becomeparamount in deliveringaccuratepublichealthsurveillance whichisresponsibleforidentifyingtrends, patterns,andemerginghealththreats.Ithelps publichealthofficialstoimplementpreventive measures,respondtooutbreaks,andallocate resourceseffectivelytoprotectthehealthof communities.Accordingto***NationalFamily Health Survey(NFHS-5, 2019-21) Report*** Approximately**19.3%**ofchildrenunderfiveare stunted,**6.6%**ofchildrenunderfivearewasted (lowweightforheight),around**33.4%**ofchildren under five are underweight (low weight for age), which is a critical indicator of poor nutrition and healthandTheprevalenceofanemiaamongchildren aged 6-59 months is approximately**67.1%**.Recenttrendsalso suggest anincreasingprevalenceofobesityamong children,particularlyinurbanareas,thoughexact figures can vary based on thespecific survey and population studied. ***According to the Centers for Disease Control and Prevention (CDC)***, anthropometryprovides a valuableassessment of nutritional status in children and adults.

For basic health surveillance, we have anthropometric metrics. Anthropometry is a branch of morphometry (study of variations and changesinthe formsoforganisms)tostudiesthe size and shape of the components of biological forms and their variations in populations. It describestherelationshipbetweenthehumanbody and disease. [1]

The word Anthropometry is derived fromthe Greekwordánthrōposmeans('human') andmétron('measure') refers to the measurement ofthehumanindividual.Anthropometryinvolves the systematic measurement of the physical properties of the human body. The core elements of anthropometry are height, weight, head circumference, body mass index (BMI), body circumferencestoassessforadiposity(waist,hip, and limbs), and skinfold thickness systematic measurement of the physical properties of the humanbody.Thecoreelementsofanthropometry areheight,weight,headcircumference,bodymass index (BMI), body circumferences to assess for adiposity (waist, hip, and limbs), and skinfold thickness.

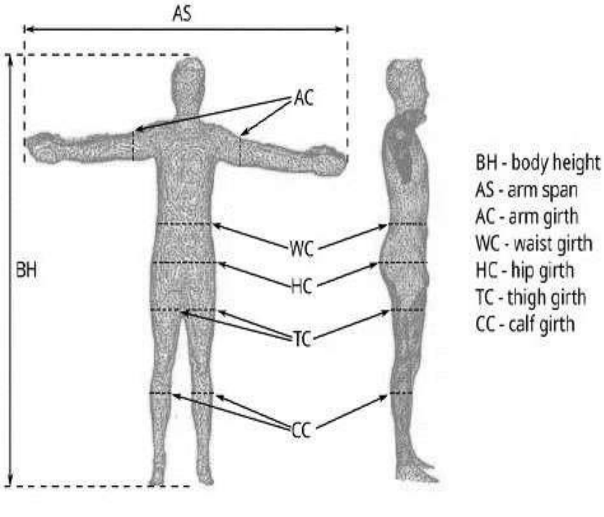


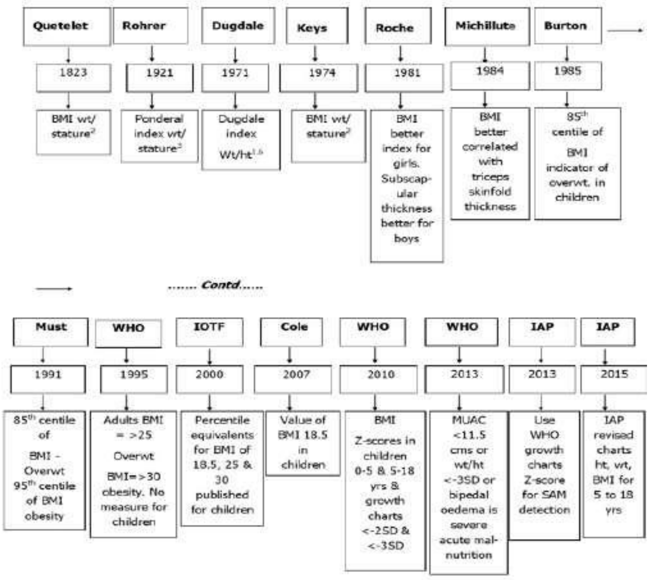
Figure1. shows the anthropometric parameters commonly used[2].

Traditionally Stadiometers for height , Anthropometersforlengthandcircumferenceofbody segments, Biocondylar calipers for bone diameter, Skinfoldcalipersforskinthicknessandsubcutaneous fat and Scales for weight are used for measuring anthropometric measurements. However in general, the accuracy of the measurements depends on the techniques used by the person taking also properly trained clinical staff is required, which makes the measurement process complicated, uncomfortable, time-consuming, and trained personnel dependent.

II. NATIONALRESEARCHONMETHODS OF ANTHROPOMETRIC MEASUREMENT USED FOR ASSESSMENT OFMALNUTRITION AMONG CHILDREN

Malnutrition among children in India remains a significantconcern,withdataindicatingthatasofthe NationalFamilyHealthSurvey(NHFS-5)conducted between2019-2021,35.5%ofchildrenunderfiveare stunted, 19.3% are wasted, and 32.1% are underweight. Child malnutrition can have profound and lasting impacts on health outcomes, affecting physical, cognitive, and emotional development.

"M. Phadke" et al [32] in their paper(published in InternationalJournalofNutritionJan2020)describes the salient landmarks in evolution of anthropometry.They mentioned thevarious methods used for anthropometric measurement from 1823-2015 as shown the figure mentioned below:



India has recorded the high prevalence of childhood undernutrition over the world (Nandy and Miranda2008;Khanand Mohanty 2018).This study showsa national review of anthropometric measuring methods used during time.Figure 2 provides a brief review of anthropometric parameters used for assessing malnutrition among children in national studies.

FiguredescribestheGeographicallocationstudied

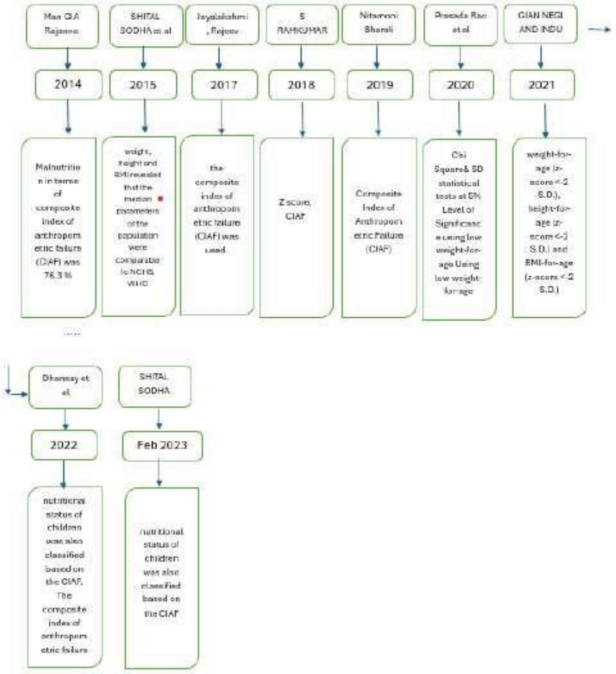


Figure defines the continuous use of CIAF for assessment of nutritional status among children.

Table1:Detailedreviewofanthropometricparametersusedwiththemethodappliedandtheircorresponding result.

Sr.no	AuthorName	TitleofPaper	Objective	Dataset	Publishing Date	MethodUsed	Result
1	*Nitamoni Bharali, Kh.NarendraSingh,NitishMondal*	**CompositeIndexof Anthropometric Failure (CIAF) amongSonowal Kachari tribal preschoolchildrenoffloodeffectedregionof Assam, India**	Toassessesthe age-sexspecificprevalence ofundernutritionusing both conventionalanthropometricmeasures and CIAF amongSonowal Kacharitribal preschoolchildren ofAssam	362(172boysand190 girls)childrenofageunder 5 years.	May 2019	Age-sexspecificZ-score value of weight-for-age,height-for-ageandweight-for-heightwerecalculatedby using WHO-Anthroand CIAF classificationwas used to calculate theprevalence of undernutrition	Theoverallprevalenceofwasting, underweight,stuntingandCIAFwasobservedtobe11.6%,22.9%, 36.2%, and 48.6%, respectively.Sex-specificprevalanceamong girls (61.05%)werefoundtobemoreaffectedthanboys(34.9%)byCIAF($p<0.01$).
2	Seetharamanet al.	Measuringmalnutrition - Therole ofZ-scores andtheCompositeIndexofAnthropometric Failure(CIAF)	Toestimatethe prevalence of undernutritionamongunder-fivechildren in Coimbatoreslums, usingtheZ-ScoresystemofclassificationandCompositeIndexofAnthropometricFailure(CIAF)	TheStudypopulation comprised of 400(0-5years) slum residingchildren	January2020	Childrenwereweighed and measured as per theWHO guidelines onanthropometry. Epi-Info2002 software packagewasusedtocalculatetheZscores and for statisticalanalysis.	Asper theZscoresystem,49.6% were underweight (21.7%severely); 48.4% were stunted(20.3%severely)and20.2% werewasted (6.9% severely). Morethan two-thirds of the childrenwere undernourished.
3	SHITAL SODHA,REKHABAJADEJAANDHASMUKHJOSHI	Anthropometric assessment of nutritional status ofadolescent girls ofPorbandar city ofGujaratstate.	The study provided the growth ,nutritionalassessment and clinicalfindingsfortheschoolbasedpopulation(15-18years)ofPorbandarcity.	studycovered100 adolescentsintheagegroup of 15-18 years.	April 2015	medianparametersofthe population were comparable to NCHS,WHO and ICMRstandards.	TheMAGexhibitedbetter nutritionalstatusintermsofweight for age, height for ageandBMIthantheOAG.
4	VIJAYETA PRIYADARSHINI* and GAYATRIBISWAL	ANTHROPOMETRY ASSESSMENTOFNUTRITIONALSTATUSOFTRIBALADOLESCENTGIRLS OF KEONJHARDISTRICT,ODISHA	Torevealthe statisticallysignificantassociationbetweennumberof family members,familyincomeandsocio-	The study was conductedinfive tribaldominatedblocksofKeonjhar (Banspal, Keonjhar,Harichandanpur,Joda,Ghatgaon)among301adolescentgirlsag	April-June 2023	Statisticalanalysissuch as arithmetic mean,standard deviation, percent distribution, andchi-square test ofindividuals according todifferent variables.	The mean BMI was 17.43351±1.059.Stunting, thinning was prevalent and age-wiseheightandweightwasfoundto be less than that of 50thpercentile of NCHS standards.Concludedtribal adolescent

			economicstatus with BMI.	ed between16and18 years.{2021-22}			girlsvulnerabletomalnutrition, anaemiaandothernutritional problems.
5	GIAN NEGI AND INDU TALWAR	NUTRITIONAL STATUSOFTRIBALPRESCHOOLCHILDREN OF DISTRICTKINNAUR,HIMACHALPRADESH	Toassessthe NutritionalstatusofTribalpre-schoolchildrenof KinnaurDistrict,HimachalPradesh.	Thecross-sectional sampleis based on 300children (150 boys and150girls)ranginginagefrom 2 to 6 years,belonging to differentvillages of Kinnaur.	2021	Indicesusedfor nutritional assessmentwere weight-for-age (z-score <-2 S.D.), height-for-age(z-score <-2S.D.)andBMI-for-age(z-score <-2 S.D.) based on WHO(2006& 2007) standards.	Theincidenceofwastingand underweight was substantiallymore than stunting. Girls showedmore stunting and wasting thanboys who were comparativelymore underweight.
6	DineshKumar etal	Nutritionstatusand associatedfactors among tribal preschool children of2-5 years in fivedistricts: a cross-sectional study fromthree states of India	Toreportthe nutritionstatus inpreschoolchildrenby2-5years of age among tribalchildrenfromfivedistricts of India.	204tribalhouseholds havingachild aged2-5year	2024 May	Themultipleregression analysis was done byusingbackwardlikelihoodratio method. The fit ofthesemodelswastestedby HosmerandLemeshowtogoodness of fit tests	Arelativelylowproportionof children were normal nutritionamong the tribal population.Socioeconomic factors, mainlythe parental education, extendedfamily were significantlyassociated with a child beingnormalnutrition.
7	AtanuAcharya 1, Gopal ChandraMandal2 ,KaushikBose3	Overallburdenof under-nutritionmeasured by aCompositeIndexinruralpre-schoolchildreninPurbaMedinipur, West Bengal,India	ToutilizeCIAF forestimatingtheoverallburdenofunder-nutritiondeterminationinpre-schoolchildren.	The115girlsand110 boys, all of Bengaleeethnicity and agedbetween 3-6 years	June 2013	Theχ2valuedetermined the significance of differences between genders.	studyrevealedthat30.7%ofthe study children suffered fromstunted growth, 42.7% wereunder-weightand12.0%wereinawasted condition. CIAF shows50.2% of the children had a high prevalence of under-nutrition.
8	Hemlata G. Rokade1 , Ashvini C. Jidge1*,Snehal S.Nadgire2	Studyofnutritional status and feedingpracticesinunderfivechildrenfromSolapurcity	Tostudythe proportion ofmalnutritionandits association withsomeofthesocio-demographicfactors	Thisisacross-sectional studyconductedin 146children under 5 yearsattending UHTC OPDduringastudyperiodof2months.	2022 Aug	Samplesizecalculated was 146 using theprevalence of 35.7% ofunderweight in SolapurdistrictasperNFHS IVat5% level of significancewith 8% margin of error.Non responseerror=10%.	Infantfeedingisthemostcrucial phase which determines theprevalence of malnutrition inchildren.

9	ManjuRani1, AtvirSingh2	SocialInequalitiesin ChildNutritioninUttar Pradesh, India	Toestimateand compare the inequalityinchildnutritionstatus across socio-demographiccharacteristicsintheUttarPradeshstate of India.	DatafromtheNational FamilyHealthSurveys(NFHS-4&NFHS-3) wasusedforUttarPradesh.	July-September 2021	Thenutritionstatuswas assessed in terms ofundernutrition (weight-forage), stunted (height-for-age), wasted (weight-for-height) and anaemialevel. SPSS.20 Used.	Despitethedecliningtrendof childhood malnutrition in UttarPradesh, the socially backwardshave a disproportionately higherburden of malnutrition.
10	Singh,Aabha; Sundaram,Shanthosh P.; Ningombam,JoennaDevi	Undernutritionanditsdeterminantsamongunder-fivechildreninatribalcommunityofMeghalaya	Todeterminethe prevalence and the factors associatedwithundernutritionamong thetribalunder-fivechildren.	196under-fivechildren residinginthevillageundertheruralfieldpracticeareaofNorthEasternIndiraGandhiRegionalInstituteofHealthandMedicalSciences(NEIGRIHMS), Meghalaya.	Jan 2024.	Anthropometric measurements, such asheight, weight, and mid-upper armcircumference,were measured for all thechildren, and Z-scoreswerecalculatedforweightforage,heightforage,andweight for height.	Therewasasignificant association for girls with wastingand education of the mother andbirth weight with stunting.
11	Chawla,Suraj et al	Undernutrition andassociatedfactors amongchildren1-5yearsofageinruralarea of Haryana,India.	Toestimatethe prevalence ofundernutritionamongunder-fivechildrenandto determine the associatedfactors.	From selected Anganwadi Centre, 20children of 15 years ofagegroupwereselectedby simple randomsampling, thus, asample of 600 childrenwas included in thestudy.	Aug 2020 .	Pearson'sChisquaretest was used. All tests wereperformedata5%level ofsignificance. Height wasmeasured by Stadiometerorinfantometer.	Childrenwithahistoryofpre-lacteal feeding had higherprevalence of stunting,underweight,andwastingthanthechildren with no history of pre-lacteal feeding.
12	Gagan Bihari Sahu	Primitivetribesand undernutrition: astudyofKatkaritribefrom Maharashtra,India	To examines nutritionalanaemiaamongKatkarichildrenandwomen.	total82children whoseageis<10	Oct 2019	WHO growth standards that includestunting (low heightfor age), wasting (lowweightforheight),andunderweight (lowweight for age) interms of Z-score	Itisobservedthatthepercentage of body fat mass increases withage up to 60–65years in bothsexesandishigherinwomenthanin men of equivalent BMI. As per CIAF, 65.4% Katkarichildrenwereundernourished
13	DebasisGhosh etal	Theprevalenceof undernutritionamongthe Santal childrenand quality of life oftheir households: astudy from hillyregion of WestBengal,India	todeterminethe prevalence of undernutritionamongtheSantalchildren of AjodhyaGram Panchayat ofPurulia district ofWest Bengal,India.	Atotalnumberof307 children aged inbetween5–10yearswere evaluated .	Mar 2021	Standardanthropometric techniques,suchasheight-for-age, weight-for-ageand body mass index for-age to determine theprevalence of stunting,wasting and underweightconditions of the Santaltribal children	Thestudyrevealstheoccurrence of undernutrition among childrenis closely associated with poorquality of life of households ofAjodhya.

14	Jayalakshmi, Rajeev; Jissa, VinodaThulaseedharan	NutritionalStatusof Mid-Day MealProgrammeBeneficiaries. ACross-sectionalStudyamong Primary Schoolchildren inKottayam District, Kerala,India	Assessed the nutritionalstatusof 6–10-year-oldschoolchildren whowerethebeneficiariesofMDMandthechild-relatedfactors.	322childrenfrom12 randomly selectedprimary schools in oneblock panchayat ofKeralastate.	Apr–Jun2017 .	thecompositeindexof anthropometric failure (CIAF) was used.	nutritionalstatusofchildrenwas not satisfactory and birth weightturned to be the important factoraffecting the nutritional status ofthese children.
15	R.ThakurandR. K.Gautam	Assessment of nutritional statusamong girls of 5-18years of age of aCentral Indian City(Sagar)	Thepresentcross-sectional study assesses the prevalence ofunder nutritionamong school-goinggirlsofcentralIndia.	Atotalof312girlsof age cohort of 5–18years were included.Height-for-age,weight-for-age and body massindexforagewereusedto evaluate theirnutritionalstatus	August6, 2015	z-scoreandcomposite index of anthropometricfailure were alsocomputed	Thestudyrevealsthatthepresent studied girlshavelowmean bodyweight andtheyareshortinstaturethan the reference population(NCHS).
16	Mohit Goyal,NidhiSingh,RichaKapoor,1AnitaVerma,1andPratimaGedam1	Assessment ofNutritionalStatusofUnder-FiveChildrenin an UrbanArea ofSouth Delhi, India	Toestimatethe prevalence ofundernutritionamongchildrenunderfiveyearsofagebyutilizingthe CIAFand theWHO growth charts.	1332childrenunder the ageoffiveyearsparticipated in afacility-based,descriptive, cross-sectional study atFatehpur Beri,UrbanPrimary Health Center.	2023 Feb	Theunder-nutritional statusofchildrenwasalsoclassifiedbasedontheCIAFusing Nandy etal.'s model of six groups	Accordingtothefindingsofthis study, the prevalence ofundernutrition among the studyparticipants was substantial
17	Dhansay1,A. N. Sharma2 andSarvendraYadav3	CompositeIndexof AnthropometricFailureamongbelowfive Children ofKorba Block,Chhattisgarh,India	Ttoassessthe nutritionalstatusbyCIAFamongbelow five childrenofKorbablock,Chhattisgarh, India	Across-sectionalstudy wasconductedamong 182 (90 male and 92female) below fivechildren in anganwadicentres of four villagespurposively.	2022	Thecompositeindexof anthropometric failurewas measured UsingSPSS.	Thestudyfurthersuggestedthe composite index ofanthropometric failure will behelpful to identify the healthdeterminants and type ofinterventionrequiredbyassessingsingle, dual or multipleanthropometricfailures.
18	S RAMKUMAR1 etal	Z-ScoreandCIAF–A Descriptive Measureto Determine Prevalence ofUnder-Nutrition in RuralSchool Children,Puducherry, India	Todeterminethe magnitude and compare the prevalence of undernutritionusingz-scoreandCIAFofruralarea.	Total792school children were enrolledfromsixschools duringNovember2013and January2014.	May 2018	Thez-score fornutritional indices were calculatedusing WHO Anthro-Software. Statistical analysis was done usingEPI-Info7.Chi-squaretestwas used to find theassociations. Ap-value	byusingCIAFclassification, undernourished children weredisseminated into differentgroups, which helps to identifychildren with multipleanthropometricfailures.

19	Krutarth R Brahmbhattetal	Role of new anthropometricindices ,validityofmuacandweech’sformulaindetectingunder-nutritionamong under-fivechildren in karnataka	Tojustifyuseof newanthropometricindicator-CIAFandthreenewindices namely UI, WI and SI.	Thestudyincluded171 children under the ageoffiveyears,whowerereferred from theanganwadis of DakshinaKannada	2012	calculatedthenew anthropometric indicesnamely SI, UI andWI.Likelihoodratioswerecalculatedfor MUACandWeech’sformula. Comparedthecommomlyused Anthroindicators interms of their sensitivity,specificity and predictivevalue	Weech’sformulaisasensitiveand specifictooltoidentifytoundernourished children
20	Prasada Rao Udaragudi1 ,SamsonSanjeeva Rao Nallapu2,TSRSai3	Assessment of Nutritional Status ofUnderfiveChildreninaLowSocio-Economic UrbanCommunityofGunturcity in AP State	To identify malnutrition inunderfivechildrenin a low socio-economic urbanarea of Gunturcity	Weightsandheights were measured for 740underfivechildren(367boys and 373 girls)according to WHOguidelines	2020	Chi Square& SD statisticaltestsat5%Level of Significanc	Usinglowweight-for-ageasthe only criterion may underestimatethe true prevalence of undernutrition.Itisalsoseenthatundernutritioninthe first yearoflife issignificantly higher both in boysandgirls.
	ManojRajanna Talapalliwar& BishanS.Garg https://link.springer.com/article/10.1007/s12098-014-1358-y	NutritionalStatusand its Correlates AmongTribal Children ofMelghat, CentralIndia	Tofindoutthe magnitude andepidemiologicaldeterminantsofmalnutritionamong0–6ytribal children.	Theinformationof540 children in the agegroup0–6ywascollected.	21 March2014	indicesofmalnutrition (underweight, stuntingand wasting) andcomposite index ofanthropometric failure(CIAF). Univariate andmultiple logistic regression analysis wereused to find out thecorrelatesofmalnutrition.	Theprevalenceofmalnutrition among these tribal children interms of underweight, stunting,and wastingwere 60.9%, 66.4%and18.8%respectively.Malnutrition in terms ofcomposite index ofanthropometric failure (CIAF)was 76.3 %

Itshowsthatoverallallcross-sectionalstudysaysthat Composite Index of Anthropometric Failure (CIAF) provides the overall magni-tude of undernutrition as an aggregate single measure over the traditional anthropometric indices and helps in identifying the prevalance of malnutition among children.

The formula for the Composite Index of Anthropometric Failure (CIAF) isCIAF =1-A/ A+ B + C + D + E + F + G + Y.

AccordingtotheCIAF,undernutritionisclassifiedas either anthropometric failure or no failure. Anthropometricfailureisfurtherdividedintosixsub-groups (labelled A-F) as follows: A – (no anthropometric failure), B – (wasting only), C – (wastingandunderweight),D–(wasting,stuntingand underweight), E – (stunting and underweight), F – (stunting only) and Y – (underweight only).

The CIAF is an anthropometric index that combines threeother indices todeterminethenutritional status of children under five years old:Weight-for-age (WAZ), Length/height-for-age (HAZ), and Weight-for-length/height (WHZ).

III. MLTECHNIQUESUSEDFOR ANTHROPOMETRIC MEASUREMENT

AItechniques, suchasML,deeplearningalgorithms (CNN,Fast CNN), Soft Computing(ANN) etc. have remarkably succeeded in various healthcare applications. These algorithms can extract intricate patterns and relationships from large scale medical datasets, enabling predictive modeling, risk stratification, and early disease detection.

Inmanyaspects of humanlifesuchascalculating nutritionalstatus[3],clinicalexaminations[4], medicine [5], dietetics [6], biomechanics [7–12], sports[13,14],andintheclothingindustry[15-18] anthropometricstudyplaysanimportantrole.The usageofanthropometrybecamepopularduetoits simplicity, non invasive procedure, ease of use, quickness,nouseofradiation,noneedforspecial instrumentation, etc.But this also comes with some drawbacks such as for the measurement of anthropometric indices we need measuring tools andproperlytrainedpersonnelwhichmakethe measurementprocesscomplicated,uncomfortable, time-consuming,andtrainedpersonneldependent [19,20].

To overcome the above challenges automatic measuring system comes into light with the help of smartphone photography [25,26], optical systems [21,22,27], sensor-based technology [23,24], and CCTV images [28]. These technologies further leverage the capabilities with the help of Machine Learning. Many studies are done to predict the anthropometric metrics usingthelatest technologies. Table below justifies the work done.

Table describes the various application areas where anthropometric parameters are used to predict hazardoushealthrisksbyapplyingMLtechniquessuch as KNN, SVM, Regression Analysis, Random Forest etc.AmongthemgenerallyusedisregressionbutSVM and RF termed best in concern with accuracy and efficiency.

IV. COCLUSION

Accuratepublichealthsurveillancereliesonhealth analysis to detect patterns, trends, and health risks. Anthropometric measures are used for basic health surveillance. Thestudy of differences inorganismal forms, with an emphasis on the size and shape of biological forms among populations, is known as anthropometry. An overview of the anthropometric measures used to measure child malnutrition in national studies is given in this paper, which also comestotheconclusionthattheCompositeIndexof Anthropometric Failure (CIAF) is a better tool than traditional measures for determining the prevalence of child malnutrition.

The paper also discusses different machine learning algorithmsthatareusedtodigitalanthropometricsin order to predict different harmful health hazards.

Sr.no	Title	Author	Objective	MLtechniqueused	Result
1	Deriving *mappingfunctions* to tieanthropometricmeasurementstobodymassindexviainterpretablemachinelearning https://doi.org/10.1016/j.mlwa.2022.100259. sciencedirect	M.Z.Naser	1) PredictingBMI 2) MappingAnthropometrictoBMI	**MLAlgorithms**:ExtremeGradientBoostedTrees, Light Gradient Boosted Trees,Random Forest, and Keras Slim ResidualNetwork. **Methods:**Mean Absolute Error (MAE),MeanAbsolutePercentageError(MAPE),Root Mean Squared Error (RMSE), andCoefficient of Determination (R2)**Database:** anthropometric measurementstaken from 252 men	ResultsfromthecurrentMLanalysisindicatethestronginfluenceofchest,abdomen, and hip on higher BMIs.(0.5–1.0, 0.3–0.5, 0.3–0.1, 0.0–0.1)
2	Height and WeightEstimationFromAnthropometricMeasurementsUsingMachineLearningRegressions doi:10.1109/JTEHM.2018.2797983 IEEE	DiegoRativa,Bruno J.T. Fernandes,andAlexandreRoque	Tostudyoftheapplicationof different learningmodels to estimate heightand weight fromanthropometricmeasurements	**MLAlgorithm:** Support Vector Regression, GaussianProcess,andArtificialNeuralNetworksarecompared. **Methods:** RootMeanSquareError(RMSE)RMSEvalue of 2.11 and an R-Squared of 0.84**Database:** Anthropometricdatacorrespondsto14783adultsubjectsfromNHANESIIIdatabase.	GaussianProcessRegression)showsthe best result in Weight andHeightprediction . ACI(confidenceinterval)of94%withlimits of 11.2cm and 13.5cm isobtainedwithconventionalregression models, whereas, a CI of 95% withlimitsof6.7cmand9.0cm,isachievedwithGPR.
3	Bodyfatpredictionthroughfeatureextractionbasedonanthropometricandlaboratory measurements 10.1371/journal.pone.0263333	ZongwenFan 2022 Feb	this study investigates theeffectiveness of featureextraction for body fatprediction. It evaluates theperformance of threefeature extractionapproaches by comparingfourwell-knownpredictionmodels.	**Algorithm**:In this study, weapplyFA, PCAandICAtoextractcriticalfeaturesusingfourmachine learning methods—MLP, SVM,Random Forest (RF) [32], and eXtremeGradient Boosting (XGBoost) [33]—topredict the body fat percentage. **Method:** We consider five metrics, that is,the mean absolute error (*MAE*), standarddeviation (*SD*), root mean square error(*RMSE*),robustness(*MAC*)andefficiency, inthe evaluation process. **Database**:252sampleswith13 input featuresandoneoutputfeature.	Among all the prediction models,XGBoost with FA for featureextraction showsthebestpredictionaccuracy(*MAE* =3.433,*SD*=4.188and *RMSE* = 4.248) XGBoost-FA performs the best forpredictingthebodyfatpercentageintermsof*MAE*,*RMSE*,*SD*and *MAC*
4	Breast CancerPredictionwithGaussianProcessUsingAnthropometric Parameters. IEEE	Sheikh Tonmoy et al 6-8 July2021	earlydeterminationofbreast cancer.	Random Forest (RF), LogisticRegression(LR), Support VectorMachine(SVM),andGaussianProcess(GP)classifiers, joined with testing unique andnovel biomarkers.	The dataset was divided into 80% forthe training phase, and 20% for thetesting phase. Results show thatGaussianProcessperformedwellwith90% test exactness on the order task.
5	PerformanceEvaluationofMachineLearningAlgorithmsforSarcopeniaDiagnosisinOlderAdults DOI:10.3390/healthcare11192699	SuÖzgür	Theaim of this study wasto identify the importantrisk factorsforsarcopeniadiagnosisandcomparetheperformance of machinelearning (ML) algorithmsin the early detection ofpotential sarcopenia	**Dataset:**involving160participantsaged65yearsandoverwhoresidedinacommunity. ML**Algorithms** wereappliedbyselecting11 features-sex, age, BMI, presence ofhypertension,presenceofdiabetesmellitus, SARC-F score, MNA score, calfcircumference (CC), gait speed, handgripstrength (HS), and mid-upper armcircumference(MUAC)-fromapoolof107clinical variables.	The highest accuracy values wereachievedbytheALL(male+female) model using LightGBM (0.931),random forest (RF; 0.927), andXGBoost (0.922) algorithms. In thefemale model, the support vectormachine (SVM; 0.939), RF (0.923), andk-nearestneighbors(KNN;0.917)algorithms performed the best.
6	AutomaticAnthropometricSystemDevelopmentUsingMachineLearning	LongTheNguyenetal	Thecontactlessautomaticanthropometric system isproposed for thereconstruction ofthe 3D-modelofthehumanbodyusing the conventionalsmartphone	GraphcutsmethodandIterativeClosestPoint (ICP) algorithm. Canny edge detectionoperator(LiyuanLi,2006)andmorphologyare used to find the body silhouette. Histogram equalizationisusedforadjustingimageintensities to enhance contrast	RFandSVM usingtheSVMclassifierandRandomForest with trees 100, 200, 300, 400, 500datasets therunningtimeofRandomForestisgreater comparing with SVM, butRandomForest provideshigheraccuracySVM.

7	HypertensionPredictioninAdolescentsUsing AnthropometricMeasurements:DoMachineLearning ModelsPerform EquallyWell?	SooSeeChaiet al 2022	Theobjectivesofthestudyare two-fold: (a)investigate the feasibility ofanthropometric measurementsandsimple demographicdatafor hypertension prediction,and (b) implement, evaluate, and analyze theperformanceofthethirteendifferent ML models for hypertensionpredictioninadolescentsusingeasy-to-collectdata.	Atotalof**2461**datasamples werecollected ... graphicdataage,gender, school, and parents' hypertension historyasinput. 90%fortraining(2215)and10%(246)for testing. **thirteenMLmodels**ofthree categories: neuralnetwork(MultilayerPerceptron), classicalmodel(LogisticRegression, DecisionTree, Naïve Bayes, k-Nearest Neighbor),andensemblemodel(Random Forest,SupportVector Machine,Gradient Boosting,XGBoost,LightGBM,CatBoost, and LogitBoost) to predict hypertension.	noneofthe13MLmodelsscoredutilizeddemo well in termsofaccuracy,precision, ethnicity, sensitivity, specificity, F1-score, misclassificationrate,and AUC.Exceptforsensitivity, LightGBM,RandomForest, CatBoost,andXGBoostarethefour best...performance criteria. ThekNNmodelbeattheother andF1-score... NaïveBayesmodel intermsof ...and logisticAdaBoost regressionmodelperformedthe best in terms of sensitivity.AdaBoost, ofAUC.Ontheother hand,theMLP model performs modestly across board,althoughitisaninteresting modelfor sensitivity.
8	PredictingtheRiskofHypertensionBasedonSeveral Easy-to-CollectRisk Factors:AMachine LearningMethod https://doi.org/10.3390/app12031600.	Zhao etal. 2021	objectives:(a) investigate thefeasibilityofanthropometric measurementsandsimple demographicdatafor hypertensionprediction, (b)implement,evaluate,and analyze the performanceofthethirteendifferent ML models for hypertensionprediction	**datasetof29,700**participantsaged ... yearsoldtodeployfour**MLmodels, namelyRandomForest(RF),CatBoost, Multi-layerPerceptron(MLP)neural network,andLogisticRegression(LR)**forhypertension risk prediction.The data were randomlydividedintotrainingand validationintheratioof4:1.Duringthe trainingstage,thetrainingsetwasdividedinto 9:1 for training and verification sets.	Onthetestset, the models' performance was measured by theArea Under Curve (AUC), accuracy, sensitivity,andspecificity.They concludedthatRF performed the best with AUC = 0.92, accuracy = 0.82, sensitivity = 0.83, and specificity =
9	Applicationof machinelearningin predictingnon-alcoholicfattyliver diseaseusing anthropometricand bodycompositionindices DOI:10.1038/s41598-023-32129-y	FarkhondehRazmpour	Aimofthisstudywastoapply machine learning(ML)methodstoidentify significantclassifiersof NAFLD using body compositionandanthropometricvariables.	among**513**individualsaged13yearsoldor aboveinIran. **ML methods** including k-Nearest Neighbor(kNN),SupportVectorMachine(SVM), RadialBasisFunction(RBF)SVM,Gaussian Process (GP), Random Forest (RF),NeuralNetwork(NN),Adaboost and NaïveBayes	RFgeneratedthemostaccuratemodel forfattyliver(presenceofanystage), steatosisstagesandfibrosisstages with82%,52%and57%accuracy, respectively.
10	MACHINE LEARNING ALGORITHMSTO PREDICTTHECHILDHOODANEMIAIN BANGLADESH	JahidurRahmanKhan etal	Topredicttheanemia statusamong children (underfiveyears)usingcommonrisk factorsasfeatures	Inthisstudy,asampleof**2013**children wereselected lineardiscriminantanalysis(LDA),classification and regression trees (CART), k-nearestneighbors(k-NN),supportvector machines(SVM),randomforest(RF)and logisticregression(LR)	RF algorithm achievedthe best classificationaccuracyof68.53% withasensitivityof70.73%, specificityof66.41%andAUCof 0.6857.Ontheotherhand,the classicalLRalgorithmreacheda classificationaccuracyof62.75% withasensitivityof63.41%, specificityof62.11%andAUCof 0.6276. Among all consideredalgorithms,thek- accuracy.

V. References

[1] Raval,H.J.,&Mehta,S.P.(2022). Anthropometric measurements: Abasisforrecordingvertical dimensionofocclusion. InternationalJournalofHealth Sciences,6(S3), 5729–5734. https://doi.org/10.53730/ijhs.v6nS3.7228

[2] KrzeszowskiT,DziadekB,FrançaC,MartinsF, GouveiaÉR,Przednowek K.SystemforEstimationof HumanAnthropometricParametersBasedonData fromKinectv2DepthCamera.*Sensors*.2023; 23(7):3459.https://doi.org/10.3390/s23073459

[3]Leandro-MerhiVA,DeAquinoJL.Anthropometric forparametersofnutritionalassessmentaspredictive factorsoftheMiniNutritionalAssessment(MNA)of thehospitalizedelderlypatients.JNutrHealthAging.2011 Mar;15(3):181-6.doi: 10.1007/s12603-010-0116-8. PMID:21369664.

[4]Jones,P., Baker,A.,Hardy,C.,Mowat,A. Measurementofbodysurfaceareainchildrenwith liverdiseasebyanovelthree-dimensionalbody scanningdevice. Eur.J.Appl.Physiol.Occup.Physiol.1994,68,514–518.[PubMed]

[5] Utkualp, Nevin&Ercan,Ilker.(2015). AnthropometricMeasurementsUsageinMedical Sciences.BioMedResearchInternational.2015.1-7. 10.1155/2015/404261.

[6]Fayet-Moore,F.;Petocz,P.;McConnell,A.;Tuck, K.;Mansour,M.Thecross-sectionalassociation betweenconsumptionoftherecommendedfivefood group"grain(cereal)",dietaryfibreandanthropometric measuresamongaustralianadults.Nutrients2017,9, 157.

[7]Choppin,S.; Wheat, J. The potential of the MicrosoftKinectinsportsanalysisandbiomechanics. Sports Technol.2013,6,78–85.

[8]MSIS,Vol. I,section 3,NASA. https://msis.jsc.nasa.gov/sections/section03.htm.

[9] BookAnthropometryandBiomechanics,1982, Volume 16,ISBN 978-1-4684-1100-3. https://link.springer.com/book/10.1007/978-1-4684-1098-3.

[10] Vigotsky,A.D.;Bryanton,M.A.;Nuckols,G.;Beardsley,C.;Contreras,B.;Evans,J.;Schoenfeld, B.J.Biomechanical,anthropometric,andpsychologicaldeterminantsofbarbellbacksquatstrength.J.StrengthCond. Res. 2019, 33, S26–S35.

[11] Dianat,I.,Molenbroek,J.,&Castellucci,H.I.(2018). Areviewofthe methodology and

applications of anthropometry in ergonomics and product design. Ergonomics, 61(12),1696–1720. https://doi.org/10.1080/00140139.2018.1502817.

[12] Xu,H.;Yu,Y.;Zhou,Y.;Li,Y.;Du,S.Measuringaccurate body parameters of dressed humans withlarge-scalemotionusingaKinectsensor.Sensors2013,13,11362–11384.

[13] Cullen S, Fleming J, Logue DM, O'Connor J,Connor B, Cleary J, Watson JA, Madigan SM.Anthropometric profiles of elite athletes. Journal ofHuman Sport and Exercise. 2022, 17(1): 145-155.https://doi.org/10.14198/jhse.2022.171.14

[14] Norton, Kevin & Olds, Tim & Olive, S. & Craig,N.P.(1996).Anthropometry and sports performance.Journal of Human Sport and Exercise. 2022, 17(1):145-155.https://doi.org/10.14198/jhse.2022.171.14

[15] Gupta, Deepti. (2014). Anthropometry and thedesign and production of apparel: An overview.10.1533/9780857096890.1.34.

[16] https://textilelearner.net/perspectives-of-anthropometry-in-garment-pattern-making/#google_vignette.

[17] Leong, Iat-Fai & Fang, Jing-Jing & Tsai, Ming.(2013). A feature-based anthropometry for garmentindustry.InternationalJournalofClothingScienceandTechnology. 25. 10.1108/09556221311292183.

[18] Rincón-Becerra,Ovidio&García-Acosta,Gabriel.(2020). Estimation of anthropometric handmeasurements using the ratio scaling method for thedesignofsewngloves.Dyna(Medellin,Colombia).87. 146-155.10.15446/dyna.v87n215.87984.

[19] Krzeszowski,T.;Dziadek,B.;França,C.;Martins,F.; Gouveia, É.R.; Przednowek, K. System forEstimation of Human Anthropometric ParametersBasedonDatafromKinectv2DepthCamera.Sensors2023, 23, 3459. https://doi.org/ 10.3390/s23073459.

[20] Thechallengesof data in future pandemicsNigelShadbolt et al in Epidemics, Vol 4,Sept 2022,00612.https://doi.org/10.1016/j.epidem.2022.100612.

[21] Wells JC et al, Acceptability, Precision andAccuracyof3DPhotonicScanningforMeasurementofBody Shape in a Multi-Ethnic Sample of ChildrenAged 5-11 Years: The SLIC Study. PLoS One. 2015Apr 28;10(4):e0124193. doi:10.1371/journal.pone.0124193. PMID: 25919034;PMCID: PMC4412635.

[22] Soileau,L &Bautista,D & Johnson,C &Gao, C&Zhang,Kang&Li,X&Heymsfield,Steven&

Thomas, Diana & Zheng, J. (2015). Automatedanthropometric phenotyping with novel Kinect-basedthree-dimensionalimagingmethod:comparisonwithareference laser imaging system. European Journal ofClinical Nutrition. 70. 10.1038/ejcn.2015.132.

[23] Espitia Contreras, Alvaro & Sanchez, PedroJose& Uribe Quevedo, Alvaro. (2014). Development of aKinect-based anthropometric measurement application.71-72.10.1109/VR.2014.6802056.

[24] WheatJS,ChoppinS,GoyalA.Develop mentandassessment of a Microsoft Kinect based system forimagingthebreastinthreedimensions.Med EngPhys.2014 Jun;36(6):732-8.doi: 10.1016/j.medengphy.2013.12.018.Epub2014Feb4. PMID:24507690.

[25] Graybeal AJ, Brandner CF, Tinsley GM.Evaluation ofautomatedanthropometricsproducedbysmartphone-based machine learning: a comparisonwithtraditionalanthropometricassessments.BrJNutr.2023 Sep 28;130(6):1077-1087. doi: 10.1017/S0007114523000090. Epub 2023 Jan 12.PMID: 36632007; PMCID: PMC10442791.

[26] Graybeal, Austin J. et al, Smartphone derivedanthropometrics: Agreement between a commerciallyavailable smartphone application and its parentapplication intended for use at point-of-care ClinicalNutrition ESPEN, Volume 59, 107 – 112.

[27] Wong MC, Bennett JP, Leong LT, Tian IY, LiuYE,KellyNN, McCarthyC,WongJMW,EbbelingCB,Ludwig DS, Irving BA, Scott MC, Stampley J, DavisB, Johannsen N, Matthews R, Vincellette C, GarberAK, Maskarinec G, Weiss E, Rood J, VaranoskeAN,Pasiakos SM, Heymsfield SB, Shepherd JA.Monitoring body composition change for interventionstudieswithadvancing3D opticalimagingtechnologyin comparison to dual-energy X-ray absorptiometry.Am J Clin Nutr. 2023 Apr;117(4):802-813. doi:10.1016/j.ajcnut.2023.02.006. Epub 2023 Feb 14.PMID: 36796647; PMCID: PMC10315406.

[28] Naufal,Ariij &Anam, Choirul &Widodo, Catur&Dougherty,Geoff.(2022).AutomatedCalculationofHeightandArea ofHuman Body for Estimating BodyWeight Using a Matlab-based Kinect Camera. SmartScience. 10. 68-75. 10.1080/23080477.2021.1983940.

[29] DoHyun Kim,JungEunKim,JiHagSong.Image-based Intelligent Surveillance System UsingUnmanned Aircraft. March 2017, Journal of KoreaMultimedia Society20(3):437-445DOI:10.9717/kmms.2017.20.3.437

[30] BOOKbyRussellS,NorvigP.ArtificialIntelligence:A Modern Approach. Prentice Hall Press: 2009.

[31] SarkerIH.Machine learning:Algorithms,real-worldapplications and research directions. SN Comput Sci.2021; 2: 160. [CrossRef]

[1] Raval, H. J., & Mehta, S. P. (2022). Anthropometricmeasurements:Aboonforrecordingvertical dimensionofocclusion.InternationalJournalofHealthSciences,6(S3),5729–5734.https://doi.org/10.53730/ijhs.v6nS3.7228.

[2] Krzeszowski T, Dziadek B, França C, Martins F,Gouveia ÉR, Przednowek K. System for Estimation ofHuman Anthropometric Parameters Based on Data fromKinect v2 Depth Camera. *Sensors*. 2023; 23(7):3459.https://doi.org/10.3390/s23073459*]*.

[3] Leandro-Merhi VA, De Aquino JL. Anthropometricparameters of nutritional assessment as predictive factorsoftheMiniNutritionalAssessment(MNA)ofhospitalizedelderly patients. J Nutr Health Aging. 2011Mar;15(3):181-6.doi: 10.1007/s12603-010-0116-8.PMID:21369664.

[4] Jones, P., Baker, A., Hardy, C., Mowat, A.Measurement of body surface area in children with liverdisease by a novel three-dimensional body scanningdevice. Eur. J. Appl. Physiol. Occup. Physiol. 1994, 68,514–518.[PubMed]

[5] Utkualp,Nevin&Ercan,Ilker.(2015).AnthropometricMeasurements Usage in Medical Sciences. BioMedResearch International. 2015. 1-7. 10.1155/2015/404261.

[6] Fayet-Moore,F.;Petocz,P.;McConnell,A.;Tuck,K.;Mansour,M.Thecross-sectionalassociationbetweenconsumption of therecommended five food group “grain(cereal)”,dietaryfibreandanthropometricmeasuresamong australian adults. Nutrients 2017, 9, 157.[7]Choppin, S.; Wheat, J. The potential of the MicrosoftKinectinsportsanalysisandbiomechanics.Sport.Technol. 2013, 6, 78–85.

[8] MSIS Vol I section 3,NASA.https://msis.jsc.nasa.gov/sections/section03.htm.

[9] BookAnthropometryandBiomechanics,1982,Volume16,ISBN : 978-1-4684-1100-3. https://link.springer.com/book/10.1007/978-1-4684-1098-3.

[10] Vigotsky, A.D.; Bryanton, M.A.; Nuckols, G.;Beardsley, C.; Contreras, B.; Evans, J.; Schoenfeld, B.J.Biomechanical, anthropometric, and psychologicaldeterminants of barbell back squat strength. J. StrengthCond. Res. 2019, 33, S26–S35.

[11] Dianat,I.,Molenbroek,J.,&Castellucci,H.I.(2018).Areviewofthemethodologyandapplicationsofanthropometry in ergonomics and productdesign. Ergonomics, 61(12),1696–1720.https://doi.org/10.1080/00140139.2018.1502817.

[1]M.Young,*TheTechnicalWriter'sHandbook*.MillValley,CA:University Science, 1989.

[12] Xu, H.; Yu, Y.; Zhou, Y.; Li, Y.; Du, S. Measuringaccurate body parameters of dressed humans with large-scale motion using a Kinect sensor. Sensors 2013, 13,11362–11384.

[13] CullenS,FlemingJ,LogueDM,O'ConnorJ, ConnorB, Cleary J, Watson JA, Madigan SM. Anthropometricprofiles of elite athletes. Journal of Human Sport andExercise. 2022, 17(1): 145-155. https://doi.org/10.14198/jhse.2022.171.14

[14] Norton, Kevin & Olds, Tim & Olive, S. & Craig,N.P.(1996).Anthropometry and sports performance.Journal of Human Sport and Exercise. 2022, 17(1): 145-155. https://doi.org/10.14198/jhse.2022.171.14

[15] Gupta,Deepti.(2014).Anthropometryandthedesignand production of apparel: An overview.10.1533/9780857096890.1.34.

[16] https://textilelearner.net/perspectives-of-anthropometry-in-garment-pattern-making/#google_vignette.

[17] Leong, Iat-Fai & Fang, Jing-Jing & Tsai, Ming.(2013). A feature-based anthropometry for garmentindustry. International Journal of Clothing Science andTechnology. 2510.1108/09556221311292183.

[18] Rincón-Becerra, Ovidio & García-Acosta, Gabriel.(2020).Estimationofanthropometrichand measurementsusing the ratio scaling method for the design of sewngloves. Dyna (Medellin, Colombia). 87. 146-155.10.15446/dyna.v87n215.87984.

[19] Krzeszowski,T.;Dziadek,B.;França,C.;Martins,F.;Gouveia, É.R.; Przednowek, K. System for Estimation ofHuman Anthropometric Parameters Based on Data fromKinectv2DepthCamera.Sensors2023,23,3459.
https://doi.org/10.3390/s23073459.

[20] The challenges of data in future pandemics NigelShadbolt et al in Epidemics, Vol 4,Sept 2022,00612.https://doi.org/10.1016/j.epidem.2022.100612.

[21] WellsJCetal,Acceptability,PrecisionandAccuracyof3DPhotonicScanningforMeasurementofBodyShapein a Multi-Ethnic Sample of Children Aged 5-11 Years:TheSLICStudy.PLoSOne.2015Apr28;10(4):e0124193.
doi: 10.1371/journal.pone.0124193. PMID: 25919034;PMCID: PMC4412635.

[22] Soileau, L & Bautista, D & Johnson, C & Gao, C &Zhang, Kang & Li, X & Heymsfield, Steven & Thomas,Diana & Zheng, J. (2015). Automated anthropometricphenotyping with novel Kinect-based three-dimensionalimaging method: comparison with a reference laserimagingsystem. European Journalof Clinical Nutrition.
70.10.1038/ejcn.2015.132.

[23] Espitia Contreras, Alvaro & Sanchez, Pedro Jose &UribeQuevedo,Alvaro.(2014).DevelopmentofaKinect-based anthropometric measurement application. 71-72.10.1109/VR.2014.6802056.

[24] Wheat JS, Choppin S, Goyal A. Development andassessment of a Microsoft Kinect based system forimaging the breast in three dimensions. Med Eng Phys.2014
Jun;36(6):732-8. doi: 10.1016/j.medengphy.2013.12.018.Epub2014Feb4. PMID:24507690.

[25] Graybeal AJ, Brandner CF, Tinsley GM. Evaluationof automated anthropometrics produced by smartphone-based machine learning: a comparison with traditionalanthropometric assessments. Br J Nutr. 2023 Sep28;130(6):1077-
1087.doi:10.1017/S0007114523000090.
Epub 2023 Jan 12. PMID: 36632007; PMCID:PMC10442791.

[26] Graybeal, Austin J. et al, Smartphone derivedanthropometrics: Agreement between a commerciallyavailablesmartphoneapplicationanditsparent applicationintended for use at point-of-care Clinical NutritionESPEN, Volume 59, 107 – 112.

[27] Wong MC, Bennett JP, Leong LT,Tian IY, Liu YE,Kelly NN, McCarthy C, Wong JMW, Ebbeling CB,Ludwig DS, Irving BA, Scott MC, Stampley J, Davis B,Johannsen N, Matthews R, Vincellette C, Garber AK,MaskarinecG,WeissE,RoodJ,VaranoskeAN,Pasiakos SM, Heymsfield SB, Shepherd JA. Monitoring bodycomposition change for intervention studies withadvancing 3D optical imaging technology in comparisontodual-energy X-rayabsorptiometry.AmJ ClinNutr.2023Apr;117(4):802-813. doi: 10.1016/j.ajcnut.2023.02.006.Epub 2023 Feb 14. PMID: 36796647; PMCID:PMC10315406.

[28] Naufal,Ariij&Anam,Choirul&Widodo,Catur&Dougherty, Geoff. (2022). Automated Calculation ofHeight and Area of Human Body for Estimating BodyWeight Using a Matlab-based Kinect Camera. SmartScience. 10. 68-75. 10.1080/23080477.2021.1983940.

[29] DoHyun Kim, Jung Eun Kim,Ji Hag Song.Image-basedIntelligentSurveillanceSystemUsingUnmanned Aircraft.March2017,JournalofKoreaMultimediaSociety20 (3):437-445
DOI:10.9717/kmms.2017.20.3.437

[30] BOOKbyRussell S,Norvig P.Artificial Intelligence:AModern Approach. Prentice Hall Press: 2009.

[31] Sarker IH. Machine learning: Algorithms, real-worldapplications and research directions. SN Comput Sci.
2021;2:160.[CrossRef]

[32] M.Phadke,R.Nair,P.Menon,V.Singal (2020)Evolutionof Anthropometry in Malnutrition. *International Journal ofNutrition* -4(4):25-35. https://doi.org/10.14302/issn.2379-7835.ijn-19-3111