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AutomatedAnthropometricParametersWithML Techniques

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***Abstract*—For basic health surveillance, we have anthropometric metrics. Anthropometry is the measurement andstudyofthehumanbodyanditsparts,particularlyfocusing on physical dimensions. This paper provides a review of automated anthropometry, its need, methods(IoT,smartphone photography,opticalsystems,sensor-basedtechnologyetc)and various ML techniques applied to medical issues and for detecting nutritional state using anthropometric parameters.**

I. INTRODUCTION

Healthanalysishasbecomeparamountindelivering accurate public health surveillance which is responsible for identifying trends, patterns, and emerginghealththreats.Ithelpspublichealthofficials to implement preventive measures, respond to outbreaks,andallocateresourceseffectivelytoprotect the health of communities.

For basic health surveillance, we have anthropometricmetrices. Anthropometricparameters arequantitativemeasurementsofthehumanbody.The keycomponentsofanthropometryareheight,weight, circumference(head ,hip, arm), body mass index (BMI)[1]. The Centers for Disease Control and Prevention(CDC)claimthatanthropometryprovides a useful evaluation of an individual's or child's nutritional health.

Numerous facets of human life depend on anthropometricmeasures,includingtheassessmentof nutritional status [2], scientific research, clinical evaluations, and medicine [3, 4], dietetics [5], biomechanics [6–8], and the apparel industry [9]. Anthropometricindexmeasurementoftenrequiresthe useofmeasuringinstrumentsandclinicalpeoplewith the necessary training, which makes the procedure difficult, inconvenient, time-consuming, and dependent on specialized individuals [10].

The challenges of medical data analysis highlights during pandemic and make researcherstoworkmore rapidly on it [11]. For the unreachable areas or pandemicregions,asystemthatisautomaticand intangible is needed. Also, every disease diagnosis required human body statistics, if it is possible to automate the measuring system the cure will be estimated earlier.

Machine learning approaches have emerged as usefulinstrumentsforresolvingthechallengesrelated to medical data processing. Flexible and adaptable approaches that can handle noise[26], uncertainties, andpartialinformationarerequiredsincemedicaldata is inherently complex and heterogeneous. ML techniques are ideally suited for tasks involving the analysis of medical data because they can handle imprecise, uncertain, and incomplete data. These methods provide accuracy in data modelling and analysisbybeingrobust,flexible,andabletomanage non-linear relationships. [12].

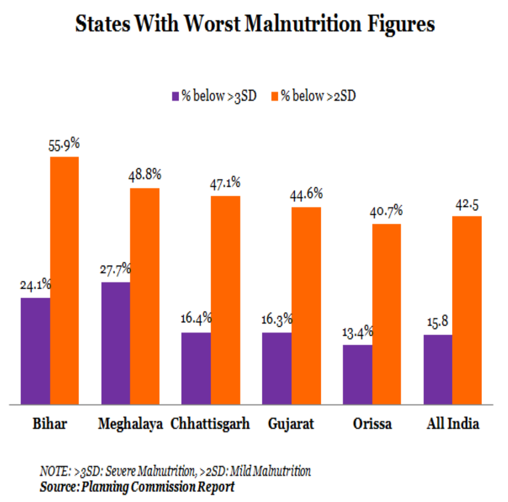
I. NEED OF AUTOMATED HEALTH SURVEILLANCE

Automatedanthropometric measurement systems are important for providingaccurateand efficient human body dimension measurements. These systems are particularly important in fields such as healthcare, where they can help assess nutritional status and detectconditionslikemalnutrition,obesity,andbeing overweight.[28]

- *Anthropometric parameters for measuring nutrition status.*

It is well known that the comfort safety and performance of people are influenced by the extent of their fitness which directly connected with the nutritional as well as environmental effects. From 2019 to 2021, 35.5% of children under five had stunting, 19.3% had wasting, and 32.1% had underweight, according to India's National Family Health Survey (NFHS-5). Fig 1 describes the nutrition status among the various states of India.

FIGURE1NUTRITIONSTATUSININDIA[13]



Malnutrition remains an underdiagnosed, underrecognizedandconsequentlyundertreatedissue. Therefore,itmustbedetectedearlier forreducingthe risks and taking necessary preventions for a healthy nation.

- *Regionswheremedicalhelpisunreachable.*

After pandemic there seen an increase in scientific interest in the creation and use of AI in medical field. Usingnewtechnologies as Rbotics, Drones, AI,MLit ispossibletoreachtheunreachableareasandmouldthe cumbersome process of measurement, which needs tools and trained staff into efficient and fastest way.

- *Anthropometricmeasuresincommercialuse*

Anthropometric measurements are important not only to calculate nutrition status but also other commercial purposes. For example, the efforts have beenmadetodesigngarments,furniture's,spaceships, toothbrushes, chairs etc. to suit effectively with varying shapes and sizes of human body.

The projections displayed in the figure 2 show an astoundingrisefromitsUSD15.1billionvaluationin 2022toastaggeringUSD355.78 billion estimate by 2032.Anastoundingdouble-digitCompoundAnnual GrowthRate(CAGR)of37.66%ispredictedbetween 2023 and 2032[14]. As there is a wide range of commercialpurposes whereanthropometricis used, if itbecameautomaticdefinitelyitwillresultingrowth of revenues in various sectors of theeconomy which impacts the overall national income.

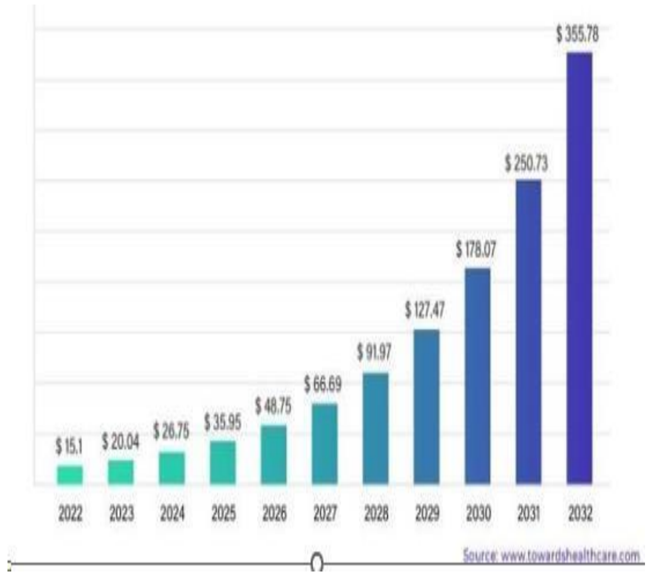


FIGURE3SHOWSAIINHEALTHCAREMARKETREVENUE2022TO2032

- *HelpinghandforClinicalStaff*

Abasic physicalexamcantakeabout30minutesto completeandbasicfullbodycheckupcantakeupto 6hourstogettheresults.Inadditionitrequires trainedclinicalstaffunder thesupervisionofexperts. Thereisagreatshortageofhealthcareworkers, especially acute in rural areas and minority communities.Figure3[15]showstheshortageof doctors in various regions of India.

FIGURE2DEPICTSTHESHORTAGEOFDOCTORSIN INDIA[15]

Automatedanthropometric studynot only helps the clinical staff but also provides a quick and efficient way for accurate body diagnosis.Enhanced accuracyandefficiencyinobtaininganthropometric measurementsimprovehealthcareoutcomesand facilitate better patient care.

II. ML TECHNIQUES USED FOR AUTOMATED ANTHROPOMETRIC MEASUREMENT

The usage of anthropometry became popular due to its simplicity, non-invasive procedure, ease of use, quickness, no use of radiation, no need for special instrumentation, etc.But this also comes with some drawbacks such as for mesauring anthropometric indices we need measuring tools and properly trained personnel which makes the measuring process complicated, uncomfortable, time-consuming and human dependent [16].

Toovercometheabovechallenges automatic measuring system comes into light with the help of IoT[17,18,25]smartphone photography [19], optical systems [16,20], sensor-based technology [21,22], and CCTV images [23]. These technologies help in gatheringautomateddatawithlesshumanintervention. further leverage the capabilities with the help of ML(Machinelearning).Itisakeycomponentofartificial intelligence that has improved healthcare byhelping doctorsdiagnoseandtreatpatientsmoreaccuratelyand efficiently.ML can also help reduce healthcare costs and improve patient outcomes.

UsingMLtechniquesdoctorscanidentifyearlysignsof disease,whichcanleadtoearlierinterventionandbetter patient outcomes, it can help doctors in analysing medical images to identify patterns that indicate a diseasealsohelpdoctors indetectingsubtlechanges in vital signs that might indicate potential health issues.

Many studies are done to predict the anthropometric metrics using the latest technologies for estimating the hazardous situations suchas cancer.Table1 justifies the work done. Python code is implemented to get the reviews, Asit is termed as most appropriate one for fetching desired data from the desired website[24].

Table1 describes the various application areas where anthropometricparametersareused topredict hazardous health risks by applying ML techniques such as KNN, SVM, Regression Analysis, Random Forest etc. Among themgenerallyusedisregressionbutSVMandRFtermed best in concern with accuracy and efficiency.

III. COCLUSION

Accurate public health surveillance relies on health analysis through anthropometry to detect patterns, trends, and health risks. The study of differences in organismal forms, with an emphasis on the size and shapeofbiologicalformsamongpopulations,isknown as anthropometry.

Automatedanthropometricmetricscapturedby2Dand 3D images providea quick, accurateand efficient way to get non-invasive and complex medical data. These data further get processed and filtered[26] for better stimation of health risks. Figure 4 shows Automated anthropometric measures with different machine learningalgorithms(KNN, SVM, Regression Analysis, Random Forest) are used to fetch digital anthropometrics in order to predict different harmful health hazards.

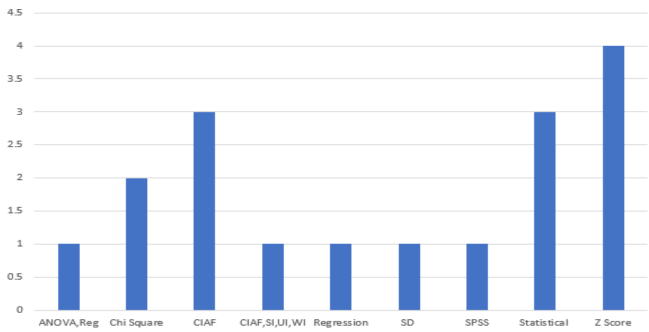


FIGURE4MLAPPLIEDINMEDICALAPPLICATIONS

IV. FUTURESCOPE

The future scope of automated anthropometric measurements is promising, with advancements in technology enabling more accurate and efficient data collection.Automatedtechniques,suchassmartphone-basedsystems,showpotentialforexceptionalprecision comparedtotraditionalmethods.Thereisalsoongoing research aimed at extracting a wide variety of measurements quickly and accurately from 3D body scans[21], addressing existing gaps in the field. This trend could lead to applications in health assessments, clothing size optimization, sports science, and ergonomic design.

For pandemic effected and unreachable areas automated anthropometrics using UAV (Unmanned Arial Vehicle) are needs to explore for better health surveillance.

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Tabel1

Sr. no	**Title**	**Objective**	**MLtechniqueused**	**Dataset**	**Result**	**Reference**
1	"Deriving *mappingfunctions* to tieanthropometricmeasurementstobodymassindexviainterpretablemachinelearning"by M.Z. Naser	1) PredictingBMI 2) MappingAnthropometrictoBMI	ExtremeGradientBoostedTrees,LightGradientBoostedTrees, RF	**252**men	Results from the current ML analysis indicatethestronginfluenceofchest,abdomen,and hipon higher BMIs. (0.5–1.0, 0.3–0.5, 0.3–0.1, 0.0–0.1)	doi.org/10.1016/j.mlwa.2022.100259. Science direct
2	"HeightandWeight EstimationFromAnthropometricMeasurementsUsingMachineLearningRegressions" byDiego Rativa et al	Topredicttheightandweightusing Anthropometry	SupportVector(SV) Regression,Gaussian,andANN	**14783** adultfromNHANESIIIdatabase.	GaussianProcessRegression)depictsthebestin Weight and Height prediction. ACIof95% withlimitsof6.7cmand9.0cm,is achieved using GPR.	doi:10.1109/JTEHM.2018.2797983 IEEE
3	"Bodyfatpredictionthroughfeatureextraction based onanthropometricandlaboratorymeasurements"byZongwen Fan et al	EstimatingbodyFat	MLP,SVM, RandomForest(RF)andXGBoost	**252**samples	XGBoostwithFAforfeatureextractionshowsthe best prediction accuracy (*MAE* = 3.433,*SD*=4.188and*RMSE*=4.248)	doi:10.1371/journal.pone.0263333.
4	"BreastCancerPredictionwithGaussianProcessUsingAnthropometricParameters" bySheikhTonmoyet al	Prediction of Breast Cancer.	RandomForest(RF), LogisticRegression(LR),SupportVector Machine(SVM),and GaussianProcess(GP)	**569**women	GaussianProcessperformedwellwith90%test exactness.	doi:10.1109/ICCCNT 51525.2021.9579704IEEE
5	"PerformanceEvaluationofMachineLearningAlgorithms forSarcopeniaDiagnosisinOlderAdults" by SuÖzgür et al	1)To identify theimportantriskfactorsrelatedsarcopeniadiagnosisandcomparetheperformanceofMLalgorithmsforthedetectingsarcopenia	LightGBM,RFand XGBoostalgorithmsformalebody and (SVM),RF and k-nearestneighborsareapplied for femalebody.	**160**participants aged65years.	Accuracy values using LightGBM is 0.931,random forest (RF) is0.927 and XGBoost is0.922forallmodels(men+women).Forfemale model, the support vector machine SVM ishaving0.939accuracy,RFishaving0.923andk-nearest neighbors (KNN) is having 0.917.	doi:10.3390/healthcare11192699
6	"DiabetesPrediction usingMachineLearningAlgorithms"byAishwaryaMujumdara et al	Toestimatediabetesusing Anthropometrymetrices.	KNN,DTC, Gaussian,LDA,SVC, LinearSVC,AdaBoost,RandomForest,ExtraTreeClassifierBagging, LogisticRegression, GradientBoost.	**800**samples	LogisticRegressiongiveshighestaccuracyof96%. AdaBoostclassifierprovedasbestmodelwithaccuracy of 98.8%	doi.org/10.1016/j.procs.2020.01.047
7	"HypertensionPredictioninAdolescentsUsingAnthropometricMeasurements :Do MachineLearning	1) To investigateanthropometricmeasurements forhypertensionpredictionand implement,	neuralnetwork ,MLP,LogisticRegression,DecisionTree,NaïveBayes,k-NearestNeighbor,	**2461**samples	ML Algorithms LightGBM, Random Forest,CatBoost,andXGBoostareleadingamongallfor sensitivity. TheKNNmodel proventhebestamongthe otherclassicalmodelsintermsofF1-scorebutlagged behind Naïve Bayes in terms of	doi:10.3390/app12031600

	ModelsPerformEquallyWell?"bySooSeeChaietal	evaluate,and analyzeMLmodels forhypertensionprediction.	RandomForest,SupportVectorMachine, GradientBoosting,XGBoost,LightGBM, CatBoost,AdaBoostandLogitBoost.		accuracy,precision,specificityand misclassificationrate. TheLogisticRegressionmodelperformedthebest in terms of sensitivity.	
8	"PredictingtheRiskofHypertensionBased on SeveralEasy-to-CollectRiskFactors: A MachineLearningMethod"byZhao et al.	Evaluateandcomparetheperformance of 4machinelearning algorithmsforpredictingtheriskofhypertension.	RandomForest(RF), CatBoost,Multi-layerPerceptron(MLP)neuralnetwork,andLogisticRegression(LR)	**29,700** participants(18-70years)	RFperformedthebestwithAUC=0.92,accuracy = 0.82, sensitivity = 0.83, andspecificity = 0.81.	https://doi.org/10.3390/app12031600.
9	"Applicationofmachinelearninginpredictingnon-alcoholicfattyliverdiseaseusinganthropometricandbodycompositionindices" byFarkhondehRazmpour et al	Toidentifyclassifiers ofNAFLDusinganthropometricindices.	k-NearestNeighbor(kNN),SupportVectorMachine(SVM),RadialBasisFunction(RBF)SVM,GaussianProcess(GP),RandomForest(RF), NeuralNetwork(NN),AdaboostandNaïve Bayes	**513**individuals (<=13years old)	RFgeneratedthemostaccuratemodelforfattyliver .	doi:10.1038/s41598-023-32129-y
10	"MachineLearningalgorithmstopredictthe childhoodanemia inBangladesh" byJahidur RahmanKhan et al	Toestimatetheanemia statusamongchildren(under5yr).	lineardiscriminantanalysis(LDA),classificationandregressiontrees(CART),k-nearestneighbors(k-NN),support vectormachines(SVM),randomforest (RF)andlogisticregression(LR)	**2013**children	RFalgorithmachievedthebestclassificationaccuracy of 68.53% with a sensitivity of70.73%, specificity of 66.41% and AUC of0.6857. Amongallconsideredalgorithms,thek-NNprovide the least accuracy.	doi:10.6339/JDS.201901_17(1).0009