**ACCIDENT DETECTION AND ALERT SYSTEM**

M.G. Santhosh Raja, Dr.M.Malathi, Mrs.S.Gospeline Christiana, Mrs.K..Nagalakshmi, Mrs.S.Sangeetha

Department of Computer Science and Engineering

Sethu Institute of Technology, Kariyapatti, Tamilnadu, India

mgsanthoshraja@gmail.com,[hodcsepg@sethu.ac.in](mailto:hodcsepg@sethu.ac.in), [sgospeline@sethu.ac.in](mailto:sgospeline@sethu.ac.in), [nagalakshmi@sethu.ac.in](mailto:nagalakshmi@sethu.ac.in), ssangeetha@sethu.ac.in

***Abstrac****t*—

Road accidents continue to be a significant global concern, resulting in loss of lives, injuries, and economic damage. In response to this pressing issue, the integration of Internet of Things (IoT) technologies has emerged as a promising solution to enhance road safety. This paper presents an IoT-based Accident Alert System designed to detect accidents in real-time and promptly notify relevant authorities and nearby vehicles to mitigate the severity of accidents and reduce response times. Leveraging sensors embedded in vehicles and road infrastructure, the system continuously monitors road conditions and vehicle movements, enabling the detection of potential accidents as they occur. Upon detection, the system automatically generates alerts containing precise accident location information, vehicle identification, and severity assessment. These alerts are transmitted to emergency services, nearby vehicles, and designated contacts through various communication channels such as Wi-Fi, cellular networks, and IoT cloud platforms. The core of the system lies in its sophisticated algorithms, which analyze sensor data to differentiate between normal driving conditions and accident scenarios accurately. Machine learning techniques are employed to continuously improve the system's accuracy in accident detection and minimize false alarms. Additionally, the integration of advanced technologies such as GPS, gyro sensors, and Wi-Fi modules enhances the system's capabilities, enabling precise positioning, motion sensing, and wireless communication. The advantages of the IoT-based Accident Alert System are manifold. Firstly, it significantly reduces emergency response times by promptly notifying relevant authorities and nearby vehicles, enabling timely medical assistance and accident management. Secondly, the system enhances road safety by alerting drivers to potential hazards and enabling proactive measures to avoid accidents. Moreover, the system's real-time monitoring capabilities provide valuable insights into traffic patterns, accident hotspots, and road conditions, facilitating data-driven decision-making for urban planning and infrastructure improvements. Despite its numerous benefits, the implementation of an IoT-based Accident Alert System also poses certain challenges. These include the need for robust communication infrastructure to ensure reliable data transmission, privacy concerns regarding the collection and sharing of sensitive information, and the integration of heterogeneous systems and devices from different manufacturers.

***Keywords***—

Internet of Things(IoT),Global Positioning System(GPS)

1. **INTRODUCTION**

The IoT-based Accident Alert project aims to revolutionize road safety by leveraging Internet of Things (IoT) technology to detect accidents in real-time and promptly alert relevant authorities and nearby vehicles. This innovative system integrates sensors installed in vehicles and road infrastructure to continuously monitor road conditions and vehicle movements. Sophisticated algorithms analyze sensor data to accurately differentiate between normal driving conditions and accident scenarios, minimizing false alarms. Upon detecting an accident, the system automatically generates alerts containing precise location information and severity assessment, which are transmitted to emergency services, nearby vehicles, and designated contacts through various communication channels such as Wi-Fi, cellular networks, and IoT cloud platforms. By enhancing emergency response times and enabling proactive measures to prevent accidents, this project aims to significantly improve road safety and mitigate the impact of accidents on lives and property.

An estimated 207,390 cases of melanoma will be diagnosed intheU.S.in2021.Ofthose,106,110caseswillbeinsitu(noninvasive),confinedtotheepidermis(thetoplayerofskin),and101,280caseswillbeinvasive,penetratingtheepidermis into the skin’s second layer(the dermis). Of theinvasive cases, 62,260 will be men and 43,850 will be women.In the past decade (2011 – 2021), the number of new invasivemelanoma cases diagnosed annually increased by 44 percent.An estimated 7,180 people will die of melanoma in 2021. Ofthose, 4,600 will be men and 2,580 will be women. Comparedwith stage I melanoma patients treated within 30 days of beingbiopsied, those treated 30 to 59 days after biopsy have a 5percent higher risk of dying from the disease, and those treatedmore than 119 days after biopsy have a 41 percent higher risk.Across all stages of melanoma, the average five-year survivalrate in the U.S. is 93 percent. The estimated five-year survivalrate for patients whose melanoma is detected early is about 99percent. The survival rate falls to 66 percent when the diseasereaches the lymph nodes [12]. It is estimated to be 106,110new cases and the chance of new cases is 5.6% and the deathrateisestimatedto be7,180and thechanceis1.2%.Thisdetailsmotivatedmetodoproceedtheprojectforhigheraccuracy.

1. **LITERATUREREVIEW**

In[1]proposesanovelTexturalsegmentationalgorithm(TDLS) is used to pinpoint the skin lesions in digital images.Fromthesegmentationresultsignificantfeatureswhichinclude, the texture features describing the different patterns ofpigmented networks, and the geometrical features based on the“ABCDscale(asymmetry,borderirregularity,colorirregularity,anddiameter)”usedinclinicaldiagnosisareextracted.SVMclassifieristrainedtoidentifylesionsasmalignant melanoma or benign lesion. The system yielded anefficiency of 84.7%, 89.4% and 83.5% for Haralick features,featuresgivenbySohandClausiandHistogrambasedfeaturesrespectively.

In [3] proposes the fully automated deep learning ensemblemethodsto achieve highsensitivity and highspecificity inlesion boundary segmentation. They segment the input imagebyusingMasterR-CNNandDeeplabv3+.InensemblemethodtheycalculatethePerformanceMetrics.Themorphologicaloperationsaredonetofilltheregionandremove unnecessary artifacts of the results.We trained theensemble methods based on Mask R-CNN and DeeplabV3+methods on ISIC-2017 segmentation training set and evaluatetheperformanceoftheensemblenetworksonISIC2017testingsetandPH2dataset.

In [6] proposes to develop and validate a multi-parameterizedartificial neural network based onavailable personal healthinformation for early detection of NMSC with high sensitivityand specificity, even in the absence of known UVR exposureand family history. This study yielded an area under the ROCcurveof0.81and0.81fortrainingandvalidation,respectively.Ourresults(trainingsensitivity88.5%andspecificity 62.2%, validation sensitivity 86.2% and specificity62.7%)werecomparableto apreviousstudy ofbasalandsquamous cell carcinoma prediction that also included UVRexposureandfamilyhistoryinformation.Theseresultsindicate that our NN is robust enough to make predictions,suggestingthatwehaveidentifiednovelassociationsandpotentialpredictiveparametersofNMSC.

In [4] proposes a new solution to solve the above issue bycreatingaboundingboxaroundtheaffectedareasanddecreasethesearchspacebyregressiontechniquewhichresults in more accuracy for classification. Methodology: Theproposedsystemconsistsofthreeparts.i)dataaugmentation

ii) boundary extraction and iii) DCNN feature extraction andselection. In the boundary extraction part, exclusive or (XOR)is used with regression technique which creates the boundingbox around the affected areas of skin lesion. It helps to reducesearch space, improve the accuracy in terms of classificationand reduce the processing time to extract the features. Results:The proposed system here is tested on PH2, ISBI 2016 and2017 datasets which has increased approx. 1.2 % of accuracycompared to state-of-art solution. The proposed system hasoutperformedthecurrentbestsolution.Whereas,thedifference is quite low, so can be further improve by testingothertypeofCNNnetworkandclassifiers.

In [9] proposes a new class of fully convolutional network isproposed, with new dense pooling layers for segmentation oflesion regions in skin images. This network leads to highlyaccurate segmentation of lesions on skin lesion datasets, whichoutperformsstate-of-the-artalgorithmsintheskinlesionsegmentation.

In [8] proposes an efficient method is necessary to detect skinlesion at the earliest. The cost of dermatoscope screening forthe patient is high, there is a need for an automated system todetect skin lesions captured using a standard digital camera.The features used in the system are extracted by using GLCM(Gray Level Co-Occurrence Matrix). The output of GLCM isgiven as the input to SVM (Support Vector Machine) classifierwhichtakestrainingdata,testingdataandgroupinginformationwhichclassifieswhethergiveninputimageiscancerousornon-cancerous.Theresultsgotarecontrast,energy,homogeneity,entropymeanare0.05570.60320.9721

0.73190.7808.

1. **PROBLEMSTATEMENT**

Many methods for segmenting Dermoscopic images have beenpresentedinthepasttwodecades.Optionalpre-processing

algorithms should applied to dermatological images includenormalizingorenhancingimagecolours.

Previous methods doesnot pinpoint the exact location of thelesionpresentintheskin.Skincancerspecialistsexaminetheir patients' skin lesions using visual inspection aided byhand-held dermoscopy. Haralick Texture features are not usedinpreviouspaperswhereTextureDistinctivenesslesionSegmentationisusedtoimprovethebestresults.

1. **EXISTINGWORK**

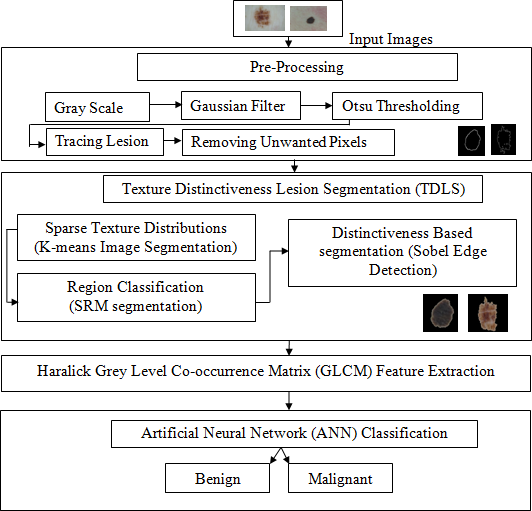
Dermatoscope is a special device for assessing the risk of skinlesionsandtheimagesacquiredthroughadigitaldermatoscopeareknownasdermoscopyimagesandearlywork on automated systems to assess the risk of melanomaused dermoscopy images. Those images pinpoint the lesionwithoutcorrectarea.TherearesomeworkdonewhereTexture Distinctiveness Lesion segmentation is used but theaccuracyremainslow.

1. **PROPOSEDWORK**

Atexturedistinctivenessbasedsegmentationalgorithmforsegmentation of skin with Haralick Grey Level Co-occurrenceMatrix(GLCM)TextureFeatureswithArtificialNeuralNetwork (ANN) is proposed. To segment the image based onthe texture by using the method of Texture Based Skin LesionSegmentation.

1. **SYSTEMARCHITECTURE**

Melanoma will be detected using the following approach. TheSystemArchitectureisasgivenbelow



## Figure1 SystemArchitecture

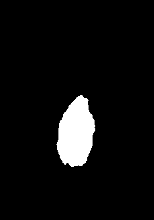
**Dataset**

## BENIGN VSMALIGNANT

ItispossibletoaccesstheBenignvs.Malignantdataset,which is open to the public and available in Kaagle website.This datasetconsistsofmorethan100imagesofeachofbenignandmalignant.Thiscanbeusedinourprojectinsucha way that it is used for the classification of the images aftersegmentation thatwhether theimageisbenignormalignant.

OtsuThresholding(*σB2)=wbwf(µb-µf)2* (3)where

wb,wf=NumberofBackgroundor foreground

µb,µf=MeanIntensityofbackgroundandforeground

## 1.Pre-processing

**7.MODULESDESIGN**

## Figure4OtsuThresholding Image

**1.4.TracingthelesionandRemoving Unwantedpixels**

It is the step where the image get transformed or encoded suchthat the machine can easily learn. Segmentation will be moredifficultinthepresenceofbrightarea.Inthispapertheprocessing consistsoffivestages.Theyare explainedbelow

## Grayscale

The color image does not help us to identify the importantedges of features. To overcome this we change the image intograyscale.Thegrayscaleoftheimageiscalculatedas

## Figure 5Tracingthelesion andremovingunwantedpixels

1. **Segmentation**

WeuseTextureDistinctivenessLesionSegmentation(TDLS)

Grayscale=(𝑅+𝐺+𝐵)

3

## Figure2GrayscaleImage

* 1. **GaussianFilter**

(1)

forsegmentingtheimage.

## 2.1.SparseTextureDistributions

Sparse texture representations [1] divide the image in sparseregions, it can be texture patches. The model learns the lesiontexture after the region detection. The problem of learning canbe a clustering or an optimization problem. The sparse texturedistributions can be determined by acquiring a texture vectorforeach pixel. Each pixel has a given no of channels. Thepixellocationisdenotedbysandthepatchcenteredatpixels

Afterthegrayscaleconversionweblurtheimageforsmoothening purpose. By doing this we remove the noise oftheimage.Theformulaisgivenas

1

isrepresentedby avectortsgiveninEqn(4).Alltexturevectors are consolidated to obtain T, which is a set of N x Mtexturevectors[2].

T={𝑡𝑠𝑗|1≤𝑗≤𝑁×𝑀} (4)

GaussianFilter=

2𝜋𝜎2𝑒

−(𝑥2+𝑦2)2𝜎

(2)

K-meansclusteringtechniqueusedtofindKclustersoftexture data points and categorize them according to similarproperties. In our case default of k means cluster is 2 since wehave 2 areas (Lesion and Non-Lesion area) in the image. Theoptimization function [2] is given in Equation. (5), where “Ckis the kth set of texture vectors, and µk is the mean vector forthe corresponding set”[10]. “The modelparameters inthe setΘmaximizethelog-likelihood functionshowninEquation.

## Figure3GaussianFilterImage

**1.3.OtsuThresholding**

In [5] Otsu divides the image into foreground and backgroundaccordingtoitsgrayscalecharacteristics.Whenthebestthreshold is taken, the difference between the two parts is thelargest.

OTSU algorithm uses the maximum inter-class variance that isrelatively common as the measure standard*.* By doing this thelesionandtheotherareaaredifferentiated.

𝐶k= argmin∑𝐾𝑘=1∑|𝑡𝑡𝑠𝑗∈𝑐𝑘𝑠𝑗−𝑢𝑘|2 (5)

AGaussiandistributionisappliedclusters.Themodelparameters used are the mean (µ), covariance (Σ) and α is themixingproportion.

Θ = argmax∑∑log(αkρ(Kk=1|µk∑k|))nj=1 (6)Where

∑𝛼𝑘 =1 ,=1andΘ={µ1,µ2,……µk,∑1,∑2,…….∑k,α1,α2,……αk}

The expectation-maximization algorithm is used which is aniterativealgorithm.Theoutputsobtainedbyk-meansclusteringareusedtoobtainthe initialparametersfortheGaussianmodel.

µk=µc𝑘 (7)

∑k=∑c𝑘 (8)

αk=ρ(𝑡𝑠𝑗€𝑐𝑘) (9)

Tomaximizetheweightedprobability𝑡𝑠𝑗|µk,∑k|eachtexture vector is allotted to belong to the distribution.From thebelow result we could observe that after applying the K-meansand Gaussian Distribution we could find the Non-Lesion are iscoveredby Yellow Regionand Lesion iscoveredby BlueRegion.



## Figure6K-meansImagesegmentationclustering

* 1. **RegionClassification**

For Region classification we do Statistical Region Merging.From the “Statistical RegionMerging (SRM) algorithm” in[11], the initial over segmentation algorithm is adapted. Theadvantage of using the SRM algorithm is that it considers thepixel location and is computationally efficient. In our projectweusesplitandmergetechniqueforStatisticalRegionMerging.

Considerthe threshold calculated earlierand let’s have theSeedvalueandpixelvalue

Theconditionisgivenas

T=abs(Seedvalue – pixelValue)<=αk (10)If the above condition is false, then split the image into 4 equalhalves.OnRepeating(10)againandagainwesplittheregion

basedonthesimilarpixelvaluesintheimageinorderto

segmenttheimage.Oncethesplittingisovermergetheregions which falls within the threshold region in the image.The merging is done in such a way that the similar regions aremerged together in such a way the lesion got segmented fromtheimage.



## Figure 7SRM Segmentation

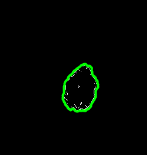
* 1. **DistinctivenessBasedSegmentation**

To achieve Distinctiveness based segmentation we first detectthe border of the lesion by using Sobel Edge Detection andsegmenttheaffectedareaintheskin.

|𝐺|=√𝑥2+𝑦2 (11)

|G|=|(P1+2\*P2+P3)-(P7+2\*P8+P9)|+|(P3+2\*P6+P9)+(P1+2\*P4+P7)|(12)

Where G is the gradient magnitude and p1, p2, p3, p4, p5, p6, p7,p8andp9arethepixelsoftheimages



## Figure8SobelEdgeDetection

Foreach texture distribution a TD metric is calculated andused to determine a regional TD metric, DR. The average TDis denoted by DR, across region R. The probability of a pixelbeing associated with the jth texture distribution is given by P(𝑇𝑗𝑟|R).

𝐷𝑅=∑𝐷𝑗𝐾𝐽=1P(𝑇𝑗𝑟|R) (13)

Otsu’s threshold [1] τ is used “to divide the set of texturedistributions” into normal skin and the lesion class. The totalintraclassvarianceisminimizedas:

τ=argmin(𝜎𝑐1(𝑟)2𝜌(𝑇𝑐1(𝑟) 𝑟)+𝜎𝑐2(𝑟) 2𝜌(𝑇𝑐2(𝑟) 𝑟) (14)

The classes depend directly on τ. The texture distribution ofskin is in class C1 (τ) if the associated distinctiveness metric isabove τ otherwise in class C2 (τ).The final segmented lesionimageisshownbelow.



## Figure9TextureBasedLesion Segmentation

1. **Featureextractionandselection**

After the segmentation the next step is feature extraction. Inthisweextractthe 10HaralickGrey LevelCo-occurrenceMatrix(GLCM)TextureFeatures[7]suchasEnergy,Contrast,Correlation,SumofAverage,SumofsquaresVariance, Cluster Prominence, Entropy, Dissimilarity, ClusterShadeandHomogeneity.

## Energy

The energy feature is used to measure the degree of pixel pairstomeasurethedisorderintextureinimages.

Energy=∑(𝑖,𝑗)2 (15)

## Contrast

Thecontrastisusedtodeterminetheamountoflocalvariations present in the images and is measured by differenceincolorandbrightness ofeachobject.

Contrast= ∑𝑖∑𝑗|𝑖− 𝑗|2(𝑖,𝑗) (16)

## Correlation

Itisusedtomeasurehowthepixeliscorrelatedwithitsneighboringpixelovertheentireimage.

paper we use Artificial Neural Network which is one of thedeep learning technique that can be used to classify the image.The classification step is illustrated in equation it is a skinlesion is abnormal or malignant if 𝑦 is 1 otherwise it signifiesnormalifyis0iftheskinlesionisbenign.

Correlation=∑𝑖∑(𝑖−𝜇𝑖)(𝑗−𝜇𝑗)𝑝(𝑖,𝑗)

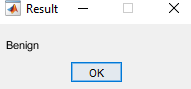
𝜎𝑖𝜎𝑗

## SumofAverage

(17)

(𝑅)={1𝑖𝑓𝐷𝑅≥𝑟(𝐿𝑒𝑠𝑖𝑜𝑛) (25)0𝑜𝑡ℎ𝑒𝑟𝑤𝑖𝑠e}

Thisisusedtomeasurethemeanofthegraylevelsum

distributionofanimage.

SumofAverage=∑2𝑁(𝑖)

(18)

𝑖=2 𝑥+𝑦

## SumofSquaresVariance

Thisisusedtomeasurethedispersionofthegraylevelsumdistributionoftheimage.

SumofSquaresVariance=∑2(𝑖−𝜇)2𝑝(𝑖,𝑗) (19)

𝑖=2

## ClusterProminence

ThisisusedtocharacterizetheclusteringofthepixelsandmeasuretheAsymmetryoftheimage.

## Figure10Resultofclassification

Theaboveimageshowstheresultofbenignfromtheclassification. If the image is found malignant the result showstheimageismalignant.

**8.CONCLUSIONANDFUTUREENHANCEMENT**

This study is carried out in Matlab 2020A environment.ThisstudyproposesHaralickGLCMFeatureswithArtificialNeuralNetwork.Fromthispaperwegotthe Accuracy of89.08%,Recallof89.58%,Precision88.00%andF1scoreas

ClusterProminence=∑𝑁𝑔−1∑𝑁𝑔−1

4 88.78%.TheEvaluationparametersasexplainedbelow.

## Entropy

𝑖=0

𝑗=0

(𝑖+𝑗−𝑢𝑥−𝑢𝑦)(𝑖,𝑗)(20)

## Accuracy:

This isusedto measurethedegreeof uniformity betweenpixels within the image and to characterize the texture of theimage.

Entropy**=-**∑𝑁𝑔−1∑𝐷−1𝑁𝑔−1(𝑖,𝑗)log(𝑝(𝑖,𝑗)) (21)

TheAccuracyisusedtocheckhowfarthevalueiscorrectlytrained.

Accuracy= 𝑇𝑟𝑢𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒+𝑇𝑟𝑢𝑒𝑁𝑒𝑔𝑎𝑡𝑖𝑣𝑒

𝑇𝑟𝑢𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒+𝑇𝑟𝑢𝑒𝑁𝑒𝑔𝑎𝑡𝑖𝑣𝑒+𝐹𝑎𝑙𝑠𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒+𝐹𝑎𝑙𝑠𝑒𝑁𝑒𝑔𝑎𝑡𝑖𝑣𝑒

𝑖=0 𝑗=0

## Dissimilarity

Thismeasuresthedistancebetweenpairsofobjectsandmeasurethegraylevelmeandifferenceintheimage.

## Precision:

Theprecisionisusedtocalculatetheratiobetweenthenumberofpositivelyclassifiedratioofimagetothetotalnumberofratioofimageclassifiedas positive.

Dissimilarity=∑∑|𝑖−𝑗|(𝑖,𝑗)

(22)

Precision= 𝑇𝑟𝑢𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒

𝑖 𝑗

## Clustershade

Thismeasurestheskewnessoftheimage andthe highervalueoccursindicatestheasymmetry

𝑇𝑟𝑢𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒+𝐹𝑎𝑙𝑠𝑒𝑁𝑒𝑔𝑎𝑡𝑖𝑣𝑒

## Recall:

The Recall used to calculate the ratio between the number ofcorrectly classified positive ratio of image to the total numberofratioofpositiveimage.

ClusterShade=∑𝑁𝑔−1∑𝐷−1𝑁𝑔−1

3 (23)

𝑖=0

## Homogeneity

𝑗=0

(𝑖+𝑗−𝑢𝑥–𝑢𝑦)

𝑝(𝑖, 𝑗)

Recall= 𝑇𝑟𝑢𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒

𝑇𝑟𝑢𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒+𝐹𝑎𝑙𝑠𝑒𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒

Thismeasurestheimagewithlargervaluesforsmallergraytonedifferenceinthepairofobject.

## F1SCORE

F1scoreisusedtocombinetheprecisionandrecallofallclassifierintothesinglemetricbytakingtheharmonicmean

Homogeneity=∑∑ 1

𝑖 𝑗 2

1+|𝑖−𝑗| (𝑖,)

## 4.Classification

(24)

and also usedto compare the performance of the classifier.Itis the product of precision and recall to the sum of precisionand recall by multiplying with 2 since there are 2 classifierusedheresuchas BenignandMalignant.

Classification is one of the major technique that is used toclassify the image inwhich the image type belongs to suchthattheimageisbenignormalignantasinourpaper.Inthis

F1Score=2\*𝑃∗𝑅

𝑃+𝑅

WherePisPrecisionandRisRecall.

TheFollowingimageshowstheperformanceratio.



**PerformanceRatio(%)**

90

89.5

89

88.5

88

87.5

87

## Figure 11Performanceoutputoftheproposed

**methodology**

The Future Enhancement of this paper consists of a TexturebasedskinLesionSegmentationalgorithmalongwithHaralick Grey Level Co-occurrence Matrix (GLCM) TextureFeatures and with Convolutional Neural Network (CNN) topinpointthelocationofthelesionwith thehigheraccuracy.

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