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A Futuristic Approach to Synaptic Fusion of Inn and CNN Architectures for Tissue Classification

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Abstract— Radiology refers to a branch of medical specialization that focuses on image processing for diagnostics. Ithasseenimmenseadvancesinpredictivemethodologiesinthe past few decades, with its predictive capacities being mostly accounted for by machine learning and deep learning approaches. However, classical machine learning has shown comparatively poor performance with regard to non-linear, irrelevant, and highly correlated features in data, and has also shownhighrelianceonproperpresentationofdata.Thispaper aims to improve that notion and aid radiological diagnostics usingadvanceddeeplearningandimageprocessingtechniques, which will eventually result in improved diagnostic accuracy and productivity of radiologists. This experiment efficiently fuses hybrid neural networks by using CNN (Convolutional Neural Network Architecture)and INN (Involutional neural networks) architectures, which was then compared with other pre-trainedmodels,trainedandtestedonmultiplecolormodels suchasRGB(Red,Green,Blue),HSV(Hue,Saturation,Value), and YCbCr (Luminance, Chrominance), to get optimal efficiency. Our proposed Convolutional Neural Network architectures, which include two fused hybrid models of INN and CNN, when trained with carefully handcrafted features, outperform other pre-trained models in terms of micro accuracy.

Keywords—*Tissue Classification, INN, CNN, Fusion Networks, Deep learning.*

I. INTRODUCTION

The cell is the most primitive form of life, capable of asexualreproduction,andnumerousfunctionalitiesincluding regulation, maintenance, and regeneration.There is a spectacular chemical processing unit inside the area that the membrane defines as its bounds [1]. Highly developed multicellularanimalsandplantshavespecializedtissuesthat can plan and control an organism's response to its environment.Inmulticellularbodies,cellscreateavarietyof tissues. Living beings have four different types of tissues: connective tissue, epithelial tissue, muscle tissue, and nerve tissue. Organ development in the body involves a variety of tissue types [2].

Tissue engineering is the procedure by which mixing of scaffolds,cellsandphysiologicallyactivechemicals,isdone, together. Damaged tissues can be repaired, improved and regenerated by assembly of useful constructions. Regenerativemedicineinvolvesself-healingstudies,and tissue engineering in its comprehension. Tissue engineering and regenerative medicine are now mainly used in an exchangeable manner, as the profession seeks to focus on cures instead of treatments for complex, often chronic, diseases.Hence,improvingclassificationofcellsandtissues canfurtheraidthefieldoftissueengineeringandregenerative medicine [3].

Thedomainsofradiology,andmedicalimaginghasseen tremendousadvancesinperspectiveofimageprocessingand digital imaging. Digital radiology is used to diagnose pathologicaldiseasesandabnormalitiesbyscanning images. Computationalpathologyisalsoatechniqueusedfrequently, to aid pathologists in this task, and can be used further to detect cancer, characterize neo vascularization, detect and classify micro lesions, and much more [4]. In this study, multiplestate-of-the-artmodelshavebeentrainedontheADP dataset,withandwithoutusingvariouscolor modelssuchas RGB,HSVetc. As inmostcases, CNNalone canturnoutto be the best solution, hence multiple CNN pre-trained and tested architectures like vgg16 [5], mobilenetv2 [6], inceptioresnetv3[7],2havebeenusedinthisstudy.Twomore customCNNmodelswhichweredesignedtofitthisparticular dataset insome cases perform better thanthe state-of-the-art pre-trained models mentioned above in terms of accuracy.

This paper has been sectioned into six components. The first section being the introduction section and the second being the literature review section with a report on related works.Thethird sectionprovidesdetailsof thedataset used, thefourthsectionbriefsthetechnologiesusedinthepaperand thefifthsectiondetailstheexperimentprocedureandanalysis derived from it. The sixth section is the acknowledgement section,followedbythereferencesectionwhichcontainsalist of the referred works.

II. LITERATUREREVIEW

The field of healthcare has seen immense involvement and development of machine learning in integration to itself, in the past years. Particularly, in fields of cancerous tissue and tumor tissue [8] classifications, deep learning models have been used and implemented extensively.In 2020, L. Saba et al. proposed a computer aided model which used optimal transfer learning approaches, namely MobileNet and Visual Geometric Group-19 (VGG-19) to detect tissues causing Wilson’sdisease[9].In2021,again,L.Sabaetal.developed

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four machine learning, one deep learning and one transfer learning architectures to characterize tissues. The mean accuracies for DL, TL, and ML over the mean of the three data sets using K10 (9:1 training to testing) were 93.55%, 94.55%, and 89%, respectively [10]. Marta Sbalgiara et al. implemented a risk-assessment scheme using a NTRK inhibition [11]. An automated process for classification of histological slides of both brain and breast tissues, utilizing GoogleInceptionV3ConvolutionalNeuralNetwork(CNN), was proposed by Justin Ker et al. The team reported a successful automated classification technique for brain histology specimens into low grade glioma (LGG), or high grade glioma (HGG). Their F1 score reported an improvement from 0.57 to 0.913 [12]. Juan S. Lara et al. explored an automated fusion approach (multi-modal) for classificationandretrievalofprostatehistopathologyimages /WSIs.Theapproachexploitedaweaklysupervisedmachine learning model which combined a bag-of-features representation, deep learning, and kernel methods. It performed excellently with an accuracy of 77.01%, thus increasingthebaselineperformanceinWSIcancerdetection by 4.74% [13]. In 2019, Quoc Dang Vu et al. proposed two machinelearningalgorithms, onedesignedforsegmentation ofnucleiandtheotheroneforforclassificationofwholeslide tissue images. The segmentation technique explored a multiscale deep residual aggregation network, and classification algorithm first implemented a patch level classification technique, followed by implementation of a RandomForest Classifier to improve accuracy. The segmentation and classification algorithms achieved accuracy scores of 78% and 81% respectively [14].More recently, in 2022, Shan Lin et al. proposed a novel, comprehensivesurgicalperceptionframework,SemanticSu-Per,whichcombinedsemanticandgeometricinformationto aiddataassociation,3dreconstructionandendoscopicscene tracking. The proposed framework was demonstrated on challenging endoscopic data with deformingtissue, highlightingitsadvantages[15].Inevenmorerecentlight,N. Dasarietal.developedamulti-scaleCNNforearlydetection of Interstitial Lung disease tissues. The model's inputs were enhanced using Gabor filter, which aided its outstanding performance with an accuracy of 99.67% [16].

Xuan Liu et al. devised a technique for automated skin tissue classification, based on optical coherence tomography(OCT).TheteamimplementedadeepCNNwith U-Netarchitectureforskinsegmentation,utilizingtheU-Net as a feature extractor in the processor. They also used SVM for detecting abnormalities in the data [17]. An end-to-end frameworkusingdeeplearningtechniqueswasproposedby H.G.Nyugenetal.in2020.Theproposedmodelwastrained to classify TMA spots into three categories: normal, epithelium and tumor tissue types. The model was an integrationoftwoeffectivedeeplearningarchitectures,CNN and capsule Network [18].

Deep learning methodologies, particularly CNN and variousCNNbasedarchitectures,includingtransferlearning have been explored extensively in terms of tissue classification. The results vary according to the architecture used,andquiteafewnumberofproposedtechniquesinclude segmentation and classification both, under a single experiment of tissue classification.

III. Dataset

Thiscomponentisdividedfurtherintotwosections,AandB, Dataset details and Dataset preprocessing respectively.

A. DatasetDetails

Fromasamplematchof500glassslides,eachmeasuring 1" X 3", a total of 100 were carefully selected. The selected slides were then scrutinised under equipment with a 20x objective lens and 0.75 numerical aperture, and they were further chosen based on the slides' few focus variations, the stains'widerangeofcolourvariations,theoriginorgans,and the diagnoses (disease / non-disease) they contained.

Following a scan of those 100 chosen slides, each slide wastransformedintoparticularrandomisedsubgroupsofnon-background patches with adiameter of1088 by1088 pixels, containing an overlap with 32 pixels. In all, 17,668 patches were accumulated. Background patches, which had greater than 97.5%ofpixels, and intensities greater than85%, inall three RGB channels, were exempted. Patches with obvious focus issues or non-tissue items, that lacked any distinguishable tissue were also removed. Each glass slide yielded an average of 177 patches (from 12 to 280).

To achieve uniform labelling, the following labelling standards were used:

- When the possibility of tissue being present anywhere in the patch, inany possible quantity, is high, non-cellular labels, or labels with singular format, are assigned;
- Cellular labels , i.e, labels with names in plural format, (e.g. "Erythrocytes") were assigned to those patches, which had cellsdetermined to be presentanywhereinit,inquantitiesof5ormore. The labels were assigned at highest specificity possible;
- Each pixel, while only correspondent to one particularmorphologicaltype,cancorrespondto another cell functionality
- Labelswereallottedatmostprimitivelevels.
- Patcheswithnodistinguishabletissuestructures were excluded from the database.

Threelevelsoftissuetypeclassificationareincludedinthe collection. The top levels have their types assigned as "Glandular" and"TransportVessel" tissues,aswellasseven morphological tissue types (a superset of five fundamental typesin,andfourfundamentalkindsin).Eachtop-leveltissue typeinthetaxonomyisfurtherbrokendownintomoreprecise sub-types, each of which either correlates to or does not correspond to a visibly distinguishable tissue type. "Undifferentiated"child nodetissues were connected withthe parent tissues nodes insituations where a more particular child node type could not be found, but we did not consider such nodes to be part of that level (due to its insufficient specificity).

B. DatasetPreprocessing

Atotalof17,668patcheswerecollectedandanalyzed.The first level consists of 9 classes: Skeletal (S), Epithelial (E), Connective Proper (C),Blood (H), Adipose (A), Muscular (M),Nervous(N),Glandular(G).Becauseofthemulti-labelled natureofthedataset,onepatchhasthepossibilityofbelonging

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tooneor more classesand labels.Thisissuecanbe resolved withthehelpofclassweightedclassification,whichwasfirst proposed by the Ziyu Xu et al. [19]

These datasets have a disproportionately high concentrationofonetypeofdatacomparedtoanother.When dealingwithsuchunbalanceddatasets,weightedclassification is frequently utilized. It is simple to obtain a high accuracy with such datasetsbymisclassifying points fromthe smaller class.Itisnotaverygoodconcepttomisclassifymembersof thesmallerclassinorderto"sacrifice"theminfavourofthose in the larger class. Utilizinga weighted classification cost to change the learned classifier's behavior, such that it gives moreweighttopointsintheminorityclassandlessweightto points inthe majorityclass, isone technique used to address thisproblem.Itisusualpracticetogiveweights,suchthatthey areinverselyproportionatetothenumberofmembersofeach class in order to achieve this result. Concisely, first observe thatP=|+1|+1,ifwedenote+1and1indexsetsforthepoints inclasses+1and1,respectively.Theseclass-wiseweightscan thenbesettobeinverselyproportionaltothenumberofpoints in each class by indicating +1 and 1 as the weights for each memberofclasses+1and1,respectively.Theassignmentof weights in classes is done as shown in eq. 1, and 2.

$$\beta{+}1= \frac{1}{|\alpha+1|} \tag{1}$$

$$\beta-1= \frac{1}{|\alpha-1|} \tag{2}$$

TABLEI. SIZESOFTRAINING,TESTINGANDVALIDATIONDATA

GeneralInformation	
Trainingsamples	14134
Validationsamples	1767
Testsamples	1767
Originaldimension	1080x1080
Level1classes	9

TABLEII. WEIGHTSGIVENTOEVERYCLASS

Label	Weight
Epithelial	1.64597648
ConnectiveProper	1.35538934
Blood	1.79867651
Skeletal	32.71759259
Adipose	26.46816479
Muscular	3.5718979
Nervous	7.59484148
Glandular	2.25243028

Table I contains information about the data-set sample size includingtrainingset,validationsetandtestingsetandtable II contains information about the weight of classes . Three distinctcolourconfigurationsknownas'colourspaces',have beenusedontheinputforbetterprocessing,namelyYCbCr, RGB and HSV.

IV. TECHNOLOGIES/SOFTWARE

Sincedeeplearning(DL)isarelativelynewfieldofstudy, it isimpossibleto provideacomprehensivereviewof all the publishedresearchonthistopic.Therefore,wehavefocused on the most important and related works.

A. *ConvolutionalNeuralNetworks(CNN)*

CNN or Convolution neural networks are a collection of deep learning networks that are primarily used for detection and classification of images. It also aids dimensionality reduction and its layers work on principles of feature extraction, which eliminates the need for implementing manual feature extraction further into the process. The input usuallyconsistsofimageswhichhaseither3channels(RGB) or1channel(GreyScale),andtheseimagesarerepresentedin matrixformswithashapeconsistingofitschannelsizeasthe last parameter. The network uses a mathematical operation, convolution,whichmultiplieseachcorrespondingelementin thematrix,toanelementinthekernel,andsumseachproduct to give the convoluted output, which is kept in a dimension-reducedmatrix.Theirapplicationsextendtohealthcare[20], agriculture[21],security[22],andmanymoreusecases.Their basic architecture is given below in fig 1.

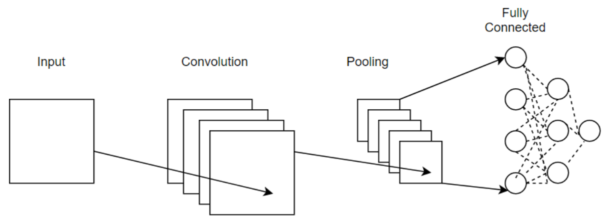

Fig.1.TypicalCNN Architecture

A typical CNN consists of 4 main types of layers – Convolution,Pooling,Flattening,andFully-Connected.Each of these layers serves to extract features, reduce spatial dimensions, convert 2d matrix to linear vectors, and to find probability of the image belonging to a particular class, respectively.Mathematically,convolutionholdstheproperty of translation equivalence, as depicted in eq 3. This implies thatcharacteristicsoftheoriginalfunctioncanbeconfigured intoanewfunction.Convolutionoperationonimage matrices can be depicted mathematically via eq 4.

$$a(b(n))=b(a(n)) \tag{3}$$

$$f*g[m]=\sum f[m-i]g[i] \tag{4}$$

Activation functions like Tanh and ReLU are used in the Fully-Connected layer, which is made using ANN(Artificial NeuralNetworks),todetermine the probabilityoftheoutput classification

B. *InvolutionalNeuralNetworks(INN)*

Involutioniscapableofusingself-attentiontoincorporate spatial model and enhance image classification.It takes advantage of nonlinear transformations in the spatial and channel domain with inverse properties G, and is uniquely designedforthepixelXi,j,R,C.Thismechanismisutilized to manage and maintain the groups of images where each groupusesaninvolutionkernel.Thefeaturemapoutputtedby theusageofsuchinvolutionkernelsisobtainedbyperforming Multiply – Add operations, which are specified as shown in eq 5.

$$Y= \sum_{(u,v)\in\Delta(k)} H_{i,j,u+\lfloor \frac{K}{2}\rfloor,v+\lfloor \frac{K}{2}\rfloor,\lceil \frac{kG}{C}\rceil} X_{i+u,+v,k.} \tag{5}$$

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Theinputfeaturemap,supposeX,determinestheformofthe involution kernels H, which are then trained on the original inputtensortoensurethattheoutputkernelsarecomfortably aligned withtheinput.The functionalmappingateachpoint (i, j) is abstracted, while the kernel-generating function is representedbythesymbolHi,j,whichisformulatedasshown in eq 6.

$$H_{i,j}=\phi(\mathbf{\Psi}_{i,j}) \tag{6}$$

where Ψi,j stores indices ofthe set of pixels, Hi,j is conditionedon.Thekernelgeneration function,asdisplayed in eq. 7.

$$\mathbf{\phi}:\mathbb{R}^{C}\rightarrow\mathbb{R}^{KXKXG} \tag{7}$$

with,$\mathbf{\Psi}_{i,j}=\{(i,j)\}$takingtheformshownineq8.

$$H_{i,j}=\phi(x_{i,j})=w_{1}\sigma(w_{0}x_{i,j}) \tag{8}$$

ThisparticularformulaassumestheimplementationofBatch normalization,aswellasnon-linearactivationfunctions.W_0,R, C_r, C, and W_1, R , (KKG) C r depict two linear transformationsasshowninequations9and10,thatconstitute a bottleneck architecture, where the intermediate channel dimension is affected by reduction ratio r, for convenient processing.

$$W_0\in\mathbb{R}^{\frac{C}{r}*C} \tag{9}$$

$$W_1\in\mathbb{R}^{(KXKXG)*(\frac{C}{r})} \tag{10}$$

The network replicates ResNet's [23] design across the full networkwithinvolutionbystackingblockswhichareresidual, on top of each other, since ResNet's architecture makes it suitable for testing out new concepts and comparing results. Theneuralnetworksoftenexperiencesignificantredundancy once spatial and channel information interact. During the kernel generation step, information stored in the dimensions of the kernel is scattered into its spatial neighborhood. Subsequently,theinformationinanenrichedreceptivefieldis gathered with the help of the enormous and dynamic involution kernels. The addition of the attention mechanism improved the performance of the encoder-decoder paradigm for machine translation.

V. RESULTSANDANALYSIS

This section provides the testing and findings fromthe data-set using multiple designs with various parameter combinations.

The best design for categorization with the lowest computing cost was selected. The experiments and findings are covered in Section A, and the assessment of the chosen architecture is covered in Section B.

A. *ExperimentalProceedings*

In this study, we have experimented with various combined architectures, fusing both CNN and INN. After intense explorations of the hyperparameters, the model was trained and tested on large data to obtain the optimal architecture.InCNN,inputsarepassedonbasisoftheshape ofthefeaturespassed,andfeatureextractionisapplied accordingly. Two variations of the experiment were carried out. In CNN, the kernel extracts the significant features by comparinganddetectingroughpatchesintheimage,withthe help of a filter / kernel. These features are represented as a matrix which is then passed to the fully connected layer for further processing and classification. In INN, feature extraction is performed by instantiating the kernel / filter at every pixel, hence taking the pixel's parameters and conditions into account.

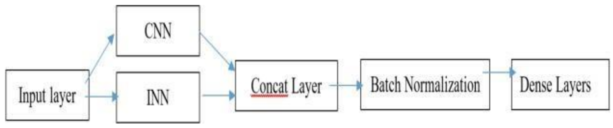

Fig.2.Variation1,InputispassedparallellytoINNandCNN

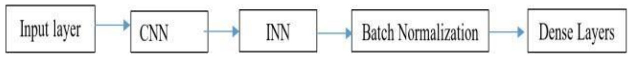

Fig.3.Variation2,InputispassedtoCNNlayer,thentotheINNlayer

Figures 2 and 3 depict the two variations of the architecturedevised forthisexperiment.Infigure3,the first variation, the input matrix/ image is passed to the CNN and INNlayerssimultaneously.Thefeaturesextractedfromboth networks are then combined into a new matrix and provided asinputto the Concatenation layer for further processing. In figure4,thesecondvariation,theinput matrixisfirstpassed totheCNNlayer,whichoutputsafeatureprobabilitymatrix. This matrix is then provided as input to the INN layers, and theoutputderivedfromthisprocessing,issentintotheDense layers ofthe fullyconnected layer for classification. For this experiment,wedeterminedthefirstarchitecture,showninfig 2,toworkbetterthanthesecond.Hence,allrecordedresults are for optimized versions of the first architecture. After finalizingthearchitecture,weconductedfurtherexperiments bytweakingotherparameterssuchasvariationinnumberof layers present in theCNN , ANN and INN , alongside regularization levels including L1 regularization and L2 regularization, image input sizes (IS), batch norm (BN), dropout layers (DO), kernel sizes (KS), and pooling matrix sizes(PS)whichlateronjudgedonthecriteriasuchasBinary accuracy (BA), Binary cross-entropy loss (BCEL), and time taken (TT) for training. The standard loss function used in classification is cross entropy loss, which was incorporated into the CNN in accordance to eq. 11.

$$Loss=\frac{1}{n}*sum(w_j*y_j*\log(y_{pred_j})) \tag{11}$$

In the above equation, $w_j$refers to the weight of the j^{th} observation,naddressesthenumberofsamples,and$y_i$refers to the actual value of the j^{th} observation. We downstream trainedthesetwoarchitectureswith5differentconfigurations bytweakingtheabove hyperparameters, for40epochseach, and obtained optimal results with ICNN-4, which provided the highest BA and lowest BCEL. Table 3 shown below, contains the results of all the configured architectures.

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TABLEIII. RESULTSRECORDEDFROMCNN,INNARCHITECTURES

S.I	CL	AL	INN	IS	Regularization		INN configuration						CNN configuration			BCEL	VBA
					L1	L2	DO	C	KS	S	RR	GN	KS	PS	S		
1	2	2	2	(128x128)	no	no	no	3	3	1	2	1	(3,3)	(2,2)	2	0.14348	87.3454
2	3	3	3	(128x128)	yes	no	yes	3	3	1	2	2	(9,3)	(4,2)	1	0.23849	83.2399
3	5	3	4	(256x256)	yes	no	no	3	3	1	2	1	(9,3)	(2,2)	1	0.31926	78.4389
4	4	3	3	(128x128)	no	yes	yes	3	3	1	2	1	(3,3)	(2,2)	2	0.1293	90.3264
5	6	4	5	(128x128)	yes	no	no	3	3	1	2	1	(9,3)	(4,2)	1	0.25349	86.4389

B. *Resultsand Analysis:*

FromtheobservationsrecordedaboveintableIII,ICNN- 4 gives optimal results as compared to the other models. It acquired a Binary Accuracy of 90.3264, and a Binary Cross Entropy Loss of 0.1293. The formulae used for calculating their precision score, recall score and F1 score have been depictedinequations12,13,and14respectively[24].These formulaehavebeenusedtocalculatedthemetricsobtainedin table V, from corresponding confusion matrices.

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

$$Recall = \frac{TP}{TP+FN} \quad (13)$$

$$F1score = \frac{2*Precision*Recall}{Precision+Recall} \quad (14)$$

TableIV,containsthemetricsobtainedforallthe9classes givenbyouroptimalarchitecture,where330nonaugmented images were considered for metric evaluation. As data augmentation was used to change the color model of the imagesandalsoresizetheimagetoacertainsize, wecannot use enlarged images for evaluation. Therefore we only considered 330 out of 17000 images for better evaluation of our optimal architecture. We also tested the same model on augmented images, but for correct and fair evaluation of the model, only the non-augmented images were considered.

TABLEIV. METRICSFORALL9METRICSOBTAINEDFROMMODELPERFORMANCEONTHEDATASET

HTT	TPR	FPR	TNR	FNR	ACC	F1	AUC
E	0.8357664234	0.1639344262	0.8360655738	0.1642335766	0.8358800226	0.863336475	0.9158449095
C	0.8408748115	0.1587301587	0.8412698413	0.1591251885	0.8409734012	0.8880923935	0.9165187442
H	0.7830474268	0.2190721649	0.7809278351	0.2169525732	0.7821165818	0.8012390294	0.8622330355
S	0.9818181818	0.001168224299	0.9988317757	0.01818181818	0.9983022071	0.972972973	0.9997557349
A	0.5277777778	0.01002949853	0.9899705015	0.4722222222	0.9711375212	0.5984251969	0.9360373648
M	0.730125523	0.08688906129	0.9131109387	0.269874477	0.8636106395	0.743343983	0.9209792548
N	0.962962963	0.007736943907	0.9922630561	0.03703703704	0.9886813809	0.9541284404	0.9969016405
G	0.897094431	0.09776833156	0.9022316684	0.102905569	0.8998302207	0.8933092224	0.9561887436
T	0.5375816993	0.2225108225	0.7774891775	0.4624183007	0.6943972835	0.5492487479	0.7275358628
Average	0.797954866	0.08229889551	0.9177011045	0.202045134	0.8749921398	0.8199275362	0.8967818685

From the above results, and the ROC curve shown below in figure 4, it is clear that our architecture showed excellent results.

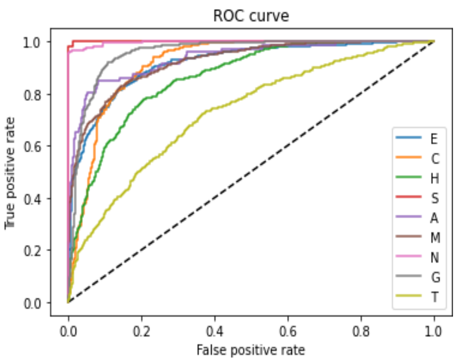

Fig.4.ROCCurveofICNN-4

VI. CONCLUSION

This paper aimed to combine two highly efficient image classificationnetworks,andfusethemtocreateamodelwhich providesoptimalcombinationsoflosses,precision,recalland F1-score. Out of the 5 different versions of the fusion architecture,whichweretested,weconfiguredchangesinthe number of layers, regularization, input shapes etc. We determined ICNN-4 to be the optimal architecture, based on its simplicity, low computational cost and specifications as stated below in table V. The boundaries and design of the chosen model were easier to configure and provided results whichweresuperiortotheothermodelsusedforcomparison. Overall, hybrid architectures provide more stable, and more efficient performances, as compared to traditional architectures.Thereisstill,however,roomforenhancement. Further evolution of AI is guaranteed to show better results.

TABLEV. SPECIFICATIONSOFTHESELECTEDARCHITECTURE

CL	AL	INN	IS	Regularization		INN configuration						CNN configuration			BCEL	VBA	Epoch
				L1	L2	DO	C	KS	S	RR	GN	KS	PS	S			
4	3	3	(128x128)	no	yes	yes	3	3	1	2	1	(3,3)	(2,2)	2	0.1293	90.3264	40

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