Industrial Engineering Journal
ISSN: 0970-2555
Volume : 49, Issue 8, July-December: 2020

ENHANCING CERVICAL CANCER OUTCOMES THROUGH EARLY DETECTION AND PREVENTION

Dr.M.Saravanan[1] , K. Keerthi[2]

[1] Professor, Department of Computer Applications, Aurora's PG College (MBA), Uppal, Hyderabad
Email: m.saravananme@gmail.com

[2]Assistant Professor, Department of Computer Applications, Aurora's PG College (MBA), Uppal, Hyderabad
Email: keerthik@gmail.com

ABSTRACT

Cervical cancer is the fourth most frequent cancer worldwide, and it mainly affects developing countries. On the other hand, clinical treatment of the patient's disease may be simpler with an early diagnosis. The problem lies in the fact that there are significantly less skilled and experienced medical cytotechnicians than there are people in need of diagnosis. utilizing computers Enhancing the diagnosis's precision, dependability, speed, and affordability can be substantially facilitated by a diagnostic system. Most existing methods require precise image segmentation in order to discern the cell. Conventional machine learning diagnostic systems function in a manner akin to that of cytopathologists, who employ morphological criteria, such as nucleus area and nucleus-cytoplasm perimeter ratio, that are manually generated to determine the malignancy of a cell. Nonetheless, this study uses convolutional neural networks (CNN).It might allow us to eliminate the segmentation and feature selection procedures, which are very computationally demanding. This study investigates the different aspects of training the CNN network with a public cervical cancer database provided by Herlev Hospital. To find the best performing optimizers, hyperparameters, and classifiers for the dataset, we also performed a comparison study.

Keywords: Convolutional Neural Networks is the keyword.

1 INTRODUCTION

Cervical cancer is primarily caused by the Human Papillomavirus (HPV), of which there are numerous strains. The HPV 16 genotype is the most carcinogenic of these. 2018 saw the reporting of about 570,000 cases of the fourth most common type of cancer, with 85% of those cases taking place in poor countries [Ferlay et al. 2019; WHOpress release]. By implementing efficient screening programs, morbidity and mortality rates can be lowered and deaths caused by the development of cervical cancer can be avoided [Schwaiger et al., 2012]. Cervical cancer screening services are relatively rare in developing countries due to a lack of finance for screening programs and a shortage of skilled and experienced healthcare staff [Mutyaba et al. 2006]. This leads to a lopsided ratio of patients to be diagnosed and treated.Along with the problem of the number of cytotechnicians, ignorance can also be regarded as one of the issues. According to Brown et al. (2012), the most widely used screening methods include liquid cytology, colposcopy, visual inspection with acetic acid, and human papillomavirus DNA testing. HPV DNA testing has shown to be a very successful

screening method, despite being costly and time-consuming [Brown et al. 2012]. Nonetheless, the papanicolaou test, sometimes known as the Pap test, is one of the most widely used methods for diagnosing cervical cancer. It entails smearing cervix cells, placing them on a slide, and looking at the cells under a microscope. Up to 300,000 cells can be seen on each slide during a pap smear examination, which makes cell segmentation challenging and time-consuming since clusters form [Chen et al. 2014].Cytologists utilize morphology, or the color and form of the cell nucleus and cytoplasm, to identify between various cell types. However, performing a visual inspection for population-wide screening requires a great deal of work, takes a long time, and requires at least two experienced cytotechnicians to make decisions. As a remedy for this problem, computer-aided diagnosing (CADx) systems have been increasingly popular over the last thirty years. It has been encouraging to see how well CADs work to lower error rates and make measurements more efficient. Because computer-aided design frameworks require tagged and annotated datasets, applying them in real-world scenarios has proven difficult despite substantial academic achievements. Creating these annotated datasets requires a lot of effort and money from a specialist [Le Lu et al. 2017]. Numerous computer vision tasks are critical to the field.Some examples of advancements that can be made in this application sector are automated detection of irregular cell morphology changes, segmentation of individual cells and cell clusters, segmentation of nuclei and cytoplasm for each cell, automated smear variation management, and artefact identification. Most CADx systems formerly used machine learning classifiers, such as Random Forest, Decision Trees, and Support Vector Machines, among others. These classifiers do, however, require constructed features and morphological qualities that are manually selected. As Summers points out, hand-tuned parameters won't be as trustworthy when CAD systems are employed to analyze fresh data [Le Lu et al. 2017]. Consequently, there would still be a difference between the training and real-testing data in a clinical setting. These hand-picked features from the training set will perform terribly when tested on real images.in a medical setting. Deep Neural Networks (DNN) or Convolutional Neural Networks (CNN) have shown a promising way to remove the notion of hand-picking the characteristics. CNNs choose abstract features that they may use to categorize the photos simply by glancing at them. In medical image processing, deep learning is still relatively new.
A key problem is that hundreds of cells are present on each slide of cells on most cervical cancer cell imaging databases. To be able to discern between the cells, it is therefore essential to have a sufficient resolving power and appropriate image resolution. The cells on the slide are stratified in numerous layers in addition to clustering in a plane, making their detection much more challenging. between the cells. Ronneberger et al. proved CNN's ability to segment cells according to pixel-level classification.However, cellular-level picture segmentation is not required because the dataset used in this work, the Herlev dataset, includes images that were captured at the level of individual cells.As deep learning advances over the coming years, it has great promise, and we can only hope that its development will parallel that of computer-aided

2.LITERATURE SURVEY AND RELATEDWORK

The process of employing algorithms to analyse data, learn from the data, and then predict the outcomes of fresh data is known as machine learning (ML). A machine is trained as opposed to other algorithms that carry out computation based on a set of instructions to complete a certain task. utilising a lot of data and algorithms that let it to carry out a task without being specifically instructed how to do so. Let's use an example to contrast how machine learning works with how traditional programming algorithms work when performing the same task. For instance, suppose we had to determine whether the general sentiment of the most popular posts in a given area was good or negative. Using a conventional programming strategy, we providea list of words that can be categorised as positive or negative by our system.A type of artificial neural network called convolutional neural networks has been extensively employed for image analysis. Since CNNs can recognise patterns in the data, picture analysis benefits greatly from their use.The 'convolutional' layer, one of the CNN's hidden layers, sets it apart from other ANNs. Training can change the weights and biases of the neurons in these layers. In subsequent subsections, the various CNN layers are described.

In their research work "Early Detection And Prevention Of Cancer Using Data Mining Techniques," P. Ramachandran, N. Girija, and T. Bhuvaneswari develop a method for determining cancer risk factor based on variables like family history and education among others using k means and clustering.

DiptiN. Punjani and Dr. Kishor H. Atkotiya in their study "Cervical Cancer Prediction Using Data Mining" go into detail on the definition of cervical cancer and associated factors. The publication also provides a thorough discussion of data mining techniques, including their applications, categories, and purposes.

Breast cancer prediction was worked on using the C4.5 and ID3 algorithms in the publication "Breast Cancer Prediction Using Data Mining Techniques" by S. Padma Priya and P. Sowmiya. These categorization algorithms are covered in detail in the survey.

Convolutions are an operation that determines the integral of a two-function product. Convolution applied to photos is the result of multiplying the image vector pixel-by-pixel and adding the convolution weight matrix [Fig. 2.2]. The stride length, filter size, and number of filters are the layer's hyperparameters. The filter weights are chosen at random.via the process of training, initialised and optimised. The Pooling layer is typically inserted after the convolutional layer and is used to derive the summary statistic for a certain feature map while retaining spatial invariance. Depending on the type of pooling utilised, they output an upsampled or downsampled version of the feature maps from the previous layer when they are added to the model.Max Pooling is a popular form of pooling.In contrast to Average Pooling, which determines the average value for the input image pixels within the kernel, it produces the maximum values of the image pixels within the kernel. In order to include non-linearity into the system and make neural networks universal approximators, activation functions are used. This allows neural networks to mimic difficult tasks. They decide whether or not a neuronsend the signal out. Without activation functions, neural networks would simply be linear combinations of weights and biases, akin to linear regressions.

3 PROPOSED WORK AND ALGORITHM

A model that has been trained for one task is repurposed for a different, related task using the machine learning technique known as transfer learning. When modelling the second task, transfer learning is an optimisation that enables quick advancement or improved performance. In essence, training a CNN entails determining the proper values for each filter so that when an input image is sent through the various layers, specific neurons in the final layer are activated to predict the correct class.Although it is possible to train a CNN from scratch for modest projects, the majority of applications call for the training of very large

CNNs, which, as you might have imagined, requires enormous amounts of processed data and computer capacity. And these days, it's harder to find both of these. Transfer learning is whenWith many high-power GPUs over several days, we take the pre-trained weights of an already trained model (one that has been trained on millions of photos belonging to thousands of classes) and utilise these already learned features to forecast new classes.

When we train a deep convolutional neural network on a dataset of images, the images are passed through the network by applying a number of filters at each layer as part of the training process. The activations of the image at each layer are multiplied by the values of the filter matrices. The last layer's activations are utilised to determine the class to which the image belongs.Our objective when training a deep network is to identify the ideal values. on each of these filter matrices so that the output activations can be utilised to precisely identify the class to which the image belongs as it is transmitted through the network. Gradient descent is the method used to determine these filter matrix values.When we train a conv net on the ImageNet dataset and examine what each filter on the conv net has learned to recognise or what triggers it, we can observe some really intriguing things.Colours and certain horizontal and vertical lines are recognised by the filters on the convolutional network's initial few layers. Utilising the previously learned lines and colours, the following levels gradually learn to recognise simple shapes. layers. Following that, the subsequent layers pick up on textures, and after that, object parts like legs, eyes, noses, etc. The output is then produced when the last layer's filters are activated by complete objects.By applying a few thick layers to the end of a pretrained network to perform transfer learning, we may learn which combinations of the previously learned characteristics aid in recognising the objects in our new dataset. CNNs can be viewed as image feature extractors that operate automatically. While using an algorithm with pixel vectors results in significant loss of spatial interaction between pixels, CNN effectively down samples the image by first using convolution and then using a prediction layer at the last.Yann Le Cun initially introduced this idea in 1998 for the categorization of digits, where he employed a single convolution layer. Later, in 2012, Alex Net, using many convolutional layers to attain the state-of-the-art in image net, popularised it. Consequently, they are now the preferred algorithm for image classification problems going forward.

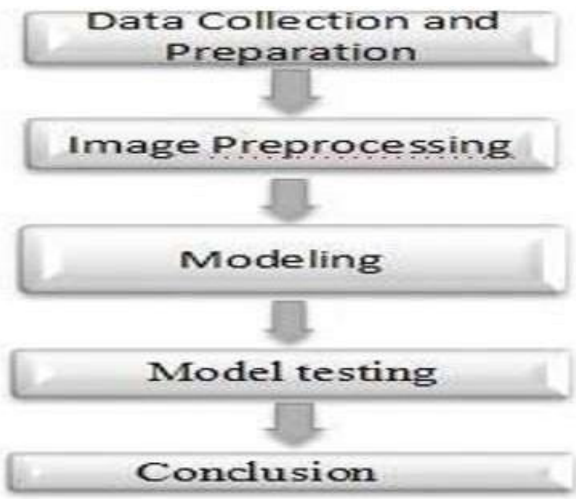


Fig:System architecture

4METHODOLOGIES

A free and open-source software library called TensorFlow is used for differentiable programming and dataflow across a variety of activities. It is a symbolic math library that is also utilised by neural network applications in machine learning. Google uses it for both research and production.The Google Brain team created TensorFlow for usage within Google. On November 9, 2015, it was made available under the Apache 2.0 open-source licence.

A general-purpose array processing package is called Numpy. It offers a multidimensional array object with outstanding speed as well as capabilities for interacting with these arrays.

It is the cornerstone Python module for scientific computing. A powerful N-dimensional array object, sophisticated (broadcasting) functions, tools for merging C/C++ and Fortran code, and useful linear algebra are only a few of the features it has. skills in algebra, Fourier transform, and random numbers

In addition to its apparent scientific applications, Numpy is a powerful multi-dimensional data container. Numpy's ability to establish any data-types makes it possible for Numpy to quickly and easily interact with a wide range of databases.

Using its potent data structures, Pandas, an open-source Python library, offers high-performance data manipulation and analysis tools. Python was mostly utilised for data preprocessing and munging. It did not make much of an impact on data analysis. Pandas figured out the solution. Regardless of the source of the data input, we may complete the five standard processes of data processing and analysis using Pandas: prepare, modify, model, and analyse. Pandas and Python are widely utilised in a variety of sectors, including academic and commercial fields including economics, statistics, analytics, and finance.

A Python 2D plotting toolkit called Matplotlib creates publication-quality graphics in a range of physical formats and in cross-platform interactive settings. Four graphical user interface toolkits, the Python and IPython shells, the Jupyter Notebook, web application servers, and Python scripts can all make use of Matplotlib. Matplotlib aims to make difficult things feasible and simple things easy. With just a few lines of code, you can create plots, histograms, power spectra, bar charts, error charts, scatter plots, and more. See the sample plots and thumbnail galleries for examples.

Particularly when used in conjunction with IPython, the pyplot package offers a MATLAB-like interface for basic plotting. You have complete control over line styles, font attributes, and axes as a power user. characteristics, etc. using a collection of MATLAB-friendly functions or an object-oriented interface.

Through a standardised Python interface, Scikit-learn offers a variety of supervised and unsupervised learning techniques. It is distributed under various Linux distributions and has a permissive simplified BSD licence, which promotes its use in both academic and commercial settings.Python is a high-level, interpreted general-purpose programming language. Python, which was developed by Guido van Rossum and originally made available in 1991, emphasises code readability and makes extensive use of white space.Python has an autonomous memory management system and a dynamic type system. It includes a sizable and thorough standard library, supports a variety of programming paradigms, including imperative, functional, procedural, and object-oriented.

Interpretation of Python Runtime processing of Python by the interpreter. Your programme does not need to be compiled before running. This is comparable to PHP and PERL.

Python is interactive; when writing programmes, you can actually sit at a Python prompt and communicate with the interpreter immediately.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 49, Issue 8, July-December: 2020

Python also acknowledges the significance of development pace. This includes having access to strong constructs that prevent laborious code repetition as well as readable and concise code. This metric's relation to maintainability is also important because it indicates how much code you must scan, read, and/or comprehend in order to fix issues or modify behaviour. This rapid evolution, the simplicity with which a programmer of another language may learn the fundamentals of Python, and the enormous standard all contribute to Another area where Python shines is libraries. All of its tools were simple to use, saved a tonne of time, and several of them could later be fixed and upgraded by non-Python experts without hurting anything.

Pandas read_csv() function for loading a dataset. Here, we'll read the data from the Excel sheet and save it to a variable.

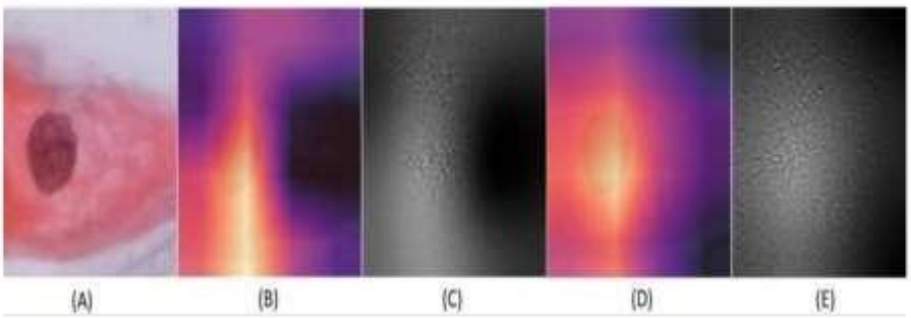
Our data set utilising the fit approach is the train-dataset. 80 percent of the dataset's data are used to train the algorithm.

Test-dataset: Use an algorithm to test the data set. 20% of the dataset's data points are used to test the algorithm.

Predict the outcomes with predict-dataset. In this step, we will forecast where the Google Play Store app will rank.

5. RESULTS AND DISCUSSION

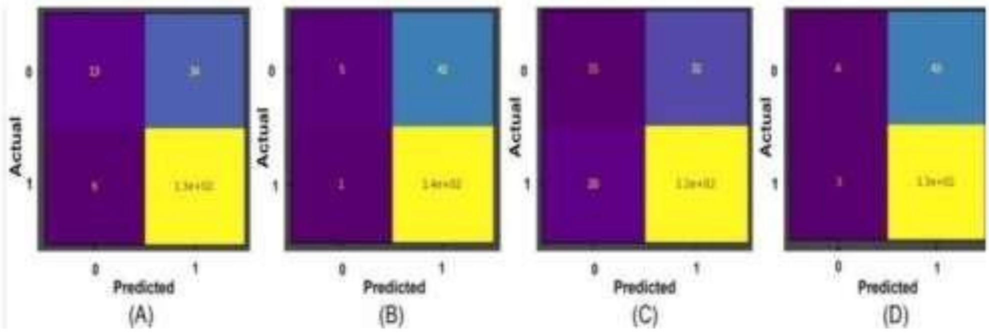
This section presents the binary classification results on the Herlev and SiPaKMeD datasets using the K-Nearest Neighbour, Stochastic Gradient Descent, Support Vector Machine, Random Forest classifier, ResNet-34, and EfficientNet-B3 models. ResNet-34 and EfficientNet-B3 models generated benchmark binary classification scores for the Herlev dataset with 98.91% accuracy, 99.29% precision, 98.92% recall, 98.91% specificity, and 99.10% F1-Score and 99.01% accuracy, 99.15% precision, 98.89% recall, 99.02% specificity, and 98.87% F-Beta score, respectively. The results of binary classification experiments using the K-Nearest Neighbour, Stochastic Gradient Descent, Support Vector Machine, Random Forest classifier, ResNet-34, and EfficientNet-B3 models. the binary classification of an aberrant single-cell picture using the Resnet-101 and Resnet-34 CNNs, which were trained on the Herlev dataset and the SIPaKMeD dataset, respectively.



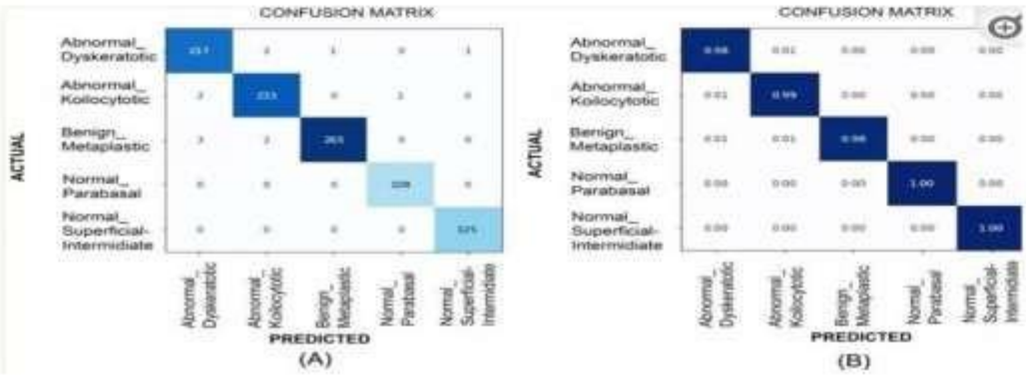
The binary classification predictions produced for a single-cell image by Resnet-101 (trained on the Herlev dataset) and Resnet-34 (trained on the SIPaKMeD dataset).For an aberrant single-cell picture input, the Resnet-101 and Resnet-34 CNN gave predictions with 99.92% and 98.94% accuracy (shown at (A)). Resnet-101 was used to obtain the Grad Cam visualisation and CNN feature interpretation, which are displayed at (B) and (C),

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 49, Issue 8, July-December: 2020

respectively. Resnet-34 is displayed at (D) and (E).



The confusion matrices for binary classification predictions at (A) Support Vector Machines, (B) Stochastic Gradient Descent, (C) K-Nearest Neighbour, and (D) Random Forest Confusion Matrices on the Herlev dataset.



The confusion matrices at (A) and the generalised score at (B) for the SiPaKMeD dataset's multi-class classification results using the EfficientNet-B3 model.The benchmark classification score emphasises the best outcomes attained by combining Progressive Resizing with Transfer Learning.

6.CONCLUSION

Considering the achieved classification accuracy, the results are not remarkable. However, it is imperative to eliminate any form of feature selection and pre-processing that requires a lot of work. The first approach to the problem yielded accuracy rates of 26.30% for seven-way classification and 73.15% for binary classification. When extra complexity and hyperparameter optimization did not improve performance, we further added convolutions to our fully connected model. Using Convolutional Neural Networks, we were able to progressively lower the error rates and achieve an accuracy of 42% for seven-way classification and 80.65% for binary classification. It was shown after multiple studies that the low quality of the data prevented feature generalization, which made system training extremely challenging.vast network starting at the bottom. Another major problem was that there were only 917 pictures in total over seven different categories in the Herlev Dataset, which made generalization very challenging. We used additional supervised learning approaches as a result of the failure of the two methods (CNN and MLP) that were previously presented. We then retrained deeper pre-trained models on our dataset using TransferLearning. Because Transfer Learning doesn't require creating models from scratch, it requires a smaller dataset. Considering the constraints of the dataset, this methodology worked perfectly.

REFERENCES

1) J. Ferlay, M. Ervik, F. Lam, M. Colombet, L. Mery, M. Pineros, et al., “Global cancer observatory: Cancer today,” Lyon, France: International Agency for Research on Cancer,2018.

2) P. Release, “Latest world cancer statistics Global cancer burden rises to 14 . 1 million new cases in 2012 : Marked increase in breast cancers must be addressed.,” Int. Agency Res. Cancer, World Heal.Organ., no. December, pp. 2012–2014, 2013

3) T. Mutyaba, F. A. Mmiro, and E. Weider pass, “Knowledge, attitudes and practiceson cervical cancer screening among the medical workers of Mulago Hospital, Uganda,” BMC Med. Educ., vol. 6, 2006

4) Alaina J. Brown, M.D.1 and Cornelia L. Trimble, Best Pract Res Clin ObstetGynaecol. 2012 April ;26(2): 233–242. doi:10.1016/j.bpobgyn.2011.11.001.

5) Teresa Conceição, Cristiana Braga, Luís Rosado and Maria João M. Vasconcelos “ A Review of Computational Methods for Cervical Cells Segmentation and Abnormality Classification”,Int. J. Mol. Sci. 2019

6) Le Lu et al. (eds.), Deep Learning and Convolutional Neural Networks for MedicalImage Computing, Advances in Computer Vision and Pattern Recognition.SpringerInternational Publishing, Switzerland 2017

7) Olaf Ronneberger, Philipp Fischer, and Thomas Brox 2015 ; U-Net: Convolutional Networks for Biomedical Image Segmentation; arXiv:1505.04597v1

8) Bora, K.; Chowdhury, M.; Mahanta, L.B.; Kundu, M.K.; Das, A.K. Automated classification of Pap smear images to detect cervical dysplasia. Comput. Methods Progr. Biomed. 2017

9) Zhang, L.; Lu, L.; Nogues, I.; Summers, R.M.; Liu, S.; Yao, J. DeepPap: Deep Convolutional Networks for Cervical Cell Classification. IEEE J. Biomed. Health Inf. 2017

10) Lin, H.; Hu, Y.; Chen, S.; Yao, J.; Zhang, L. Fine-Grained Classification of CervicalCells Using Morphological and Appearance Based Convolutional Neural Networks

11) J. Jantzen, J. Norup, G. Dounias, and B. Bjerregaard, "Pap-smear benchmark datafor pattern classification," Nature inspired Smart Information Systems (NiSIS 2005), pp. 1–9, 2005

12) D. Solomon and R. Nayar, The Bethesda System for reporting cervical cytology: definitions,criteria, and explanatory notes. Springer Science & Business Media, 2004.

13) Ronneberger, O., Fischer, P., and Brox, T. (2015). "U-Net: convolutional networks for biomedical image segmentation," in International Conference on MedicalImage Computing and Computer Assisted Intervention (Munich), 234–241.

14) Burnham, K. P.; Anderson, D. R. (2002), Model Selection and Multimodel Inference (2nded.), Springer-Verlag.

15) He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: CVPR. (2016)

16) C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. Rethinking the inception architecture for computer vision. arXiv preprint arXiv:1512.00567, 2015

17) C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception- resnet and the impactof residual connections on learning," in International Conference Learning Representations (ICLR) Workshop, 2016

18) Nesterov, Y. (1983). A method for unconstrained convex minimization problem with the rate of convergence o(1/k2). Doklady ANSSSR

19) Geoffrey Hinton. 2012. Neural Networks for Machine Learning - Lecture 6a - Overview of mini- batch gradient descent.

20) Kingma, D. P., & Ba, J. L. (2015). Adam: a Method for Stochastic Optimization. International Conference on Learning Representations,

21) Chankong T, Theera-Umpon N, Auephanwiriyakul S. Automatic cervical cell segmentation and classifcation in Pap smears. Comput Methods Programs Biomed.2014

22) Journal I, Applications C, Bangalore- T. Papsmear image based detection ofcervical cancer. Int J Comput Appl.2012

23) Ampazis N, Dounias G, Jantzen J. Pap-smear classifcation using efcient second order neuralnetwork training algorithms. Springer. 2004

24) Kangkana Bora, Manish Chowdhury, Lipi B. Mahanta, Malay K. Kundu, and Anup K. Das. 2016. Pap smear image classification using convolutional neural network. In Proceedings of the Tenth Indian Conference on Computer Vision, Graphics and Image Processing (ICVGIP '16). Associationfor Computing Machinery, New York, NY, USA, Article 55, 1–8. DOI:https://doi.org/10.1145/3009977.3010068

25) Mahdianpari, Masoud & Salehi, Bahram & Rezaee, Mohammad &Mohammadimanesh, Fariba & Zhang, Yun. "Very Deep Convolutional Neural Networks for Complex Land Cover Mapping UsingMultispectral Remote SensingImagery."Remote Sensing. Vol 10. 2018

26) Wolpert, D.H., Macready, W.G. (1997), "No Free Lunch Theorems for Optimization",IEEETransactions on Evolutionary Computation 1, 67.