An Optimized Neural Network Architecture for Auto Characterization of Biological Cells in Digital Inline Holography Micrographs

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***Abstract*— Digital inline holography (DIH) based microscopy is a proven technique for the characterization of biological cells via their diffraction signatures. Most of the prevalent characterization techniques are based on the handcrafted feature extraction methods. This limits the applicability to certain known cell types only. It needs adjustment for every new cell type, whereby features must be manually determined first, making it very tedious and prone to subjective errors. To overcome these problems, we have investigated various representational learning-based artificial neural network (ANN) architectures to classify cell types, namely, red blood cells (RBC), white blood cells (WBC), cancer cells (HepG2 and MCF7), and artificial microbeads. The performance of these ANNs on various dimensions of cell micrographs as well as across other standard machine learning algorithms have been studied to obtain an optimized model and to validate it. This study shows that the convolutional neural network (CNN) based architecture shows a better classification accuracy of ~ 97% as compared to the traditional support vector machine (SVM) based architecture with an accuracy of ~71%. These results are comparable to that of the analytical model, which shows the average classification accuracy of ~95%. Further, we can incorporate this trained model in the on-board computer of DIH based lens-free microscope to facilitate a portable telemedicine diagnosis device.**

Keywords*— *AI, DIH, CNN, SVM, Healthcare Diagnosis

I. Introduction

A. Digital Inline Holography (DIH):

The digital inline holography (DIH) is a novel imaging technique that can be utilized for the imaging of microparticles in a cost-effective setup [1]. Combined with an advanced computer vision algorithm, it can be utilized for differential characterization of cell lines [2, 3]. DIH finds a huge range of applications such as in microscopy, interferometry, and 3D-imaging of cells, tissues and microorganism samples [4]. This is due to its simple arrangement as shown in the figure1.

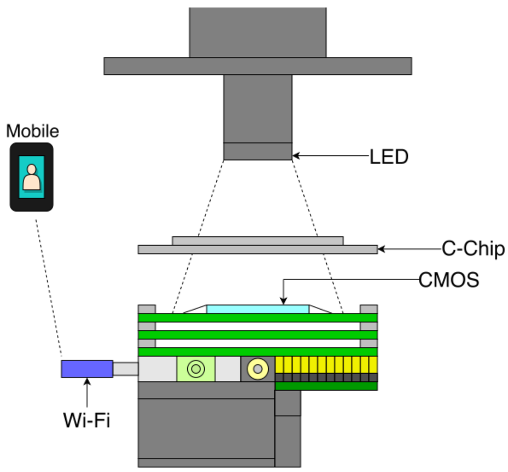

Fig 1. The schematic of a digital inline holography (DIH) setup. The figure depicts simplicity of the DIH system. The system consists of a light source, a sample holder (C-Chip) and a digital image sensor (CMOS) to record the diffraction pattern of the microparticles or cells.

The main advantage of the Digital Inline Holographic Microscopy (DIHM) imaging technique is that we can use numerical reconstruction algorithms to extract the required features of the object. This allows us to capture a variety of information about the sample, like its 3D structure and high-resolution diffraction patterns in a very wide field of view, hence, easily forms a base for the supervised type of machine learning. We can train an artificially intelligent model to learn these diffraction signatures which are characteristic of the cells and subsequently use for diagnostic testing [5].

In our work, we have developed artificial neural network architectures, based on convolutional neural network (CNN) for characterizing the different cell types, and validated and compared their performance with other traditional machine learning methods and existing analytical models. The details are as described in the following sections.

II. Methods

A. *Cell-line Preparation:*

The cell lines i.e. red blood cell (RBC), white blood cell (WBC), HepG2, MCF7 and microbead samples are prepared as described in [6] and [7].

B. *Dataset Creation:*

The dataset under study consists of six different cell lines (classes), namely, RBC, WBC, two types of cancer cells i.e. HepG2 and MCF7, and glass beads (10µm and 20µm).

This dataset is created by cropping the diffraction pattern of each cell line (of size 66×66 pixels) from a whole frame DIH micrograph (full frame), each having size 2560×1920. The diffraction signatures of the cell-types are as shown in figure 2.

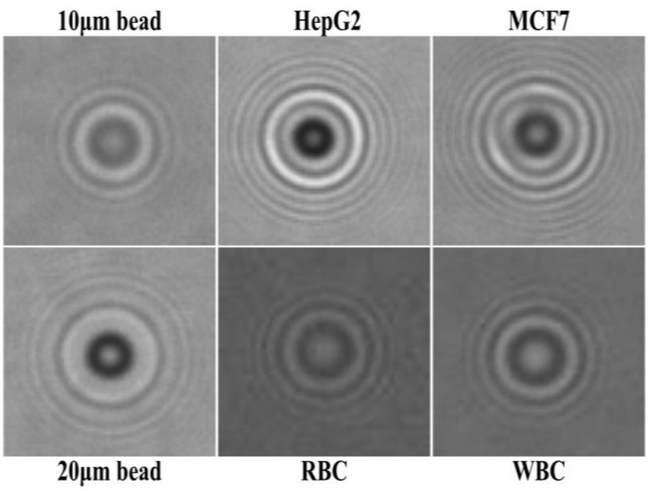

Fig 2. The diffraction pattern of each cell line cropped out (of 66 X 66 size) from the whole frame DIH micrograph

C. *Neural Network Architectures:*

Convolutional neural network (CNN) is a type of deep learning architecture used for spatial data analytics [8]. Currently, CNNs form the base for state-of-the-art method, and are very robust and widely used for most kinds of image analytics such as classification and segmentation.

In our work, we have used CNN-based architectures to classify the various cell lines from DIH micrograph. In order to determine the most optimal architecture, we first proceeded to find the optimal depth of the network by studying the classification performance of the model on increasing the depth—by adding convolutional and pooling layers—as well as breadth, by varying number of kernels and kernel size, till we reach performance saturation. We developed and evaluated various shallow and deep models to classify cell line images of various sizes.

III. Results and Discussion

A. *Results from CNN*

The effect of deepening the CNN model on the performance is shown in figure 3. From the figure, we can see that the intermediate model shows a better performance in terms of classification accuracy as well as loss.

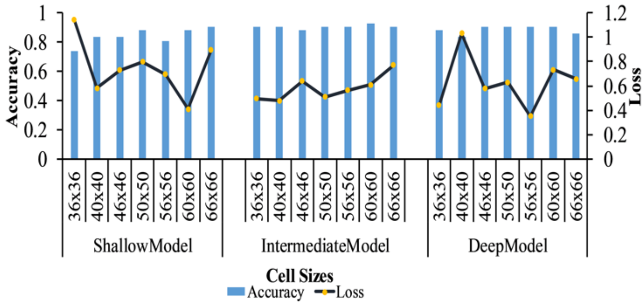

Fig 3. Performance of CNN models across various input sizes (cell diffraction pattern size). The first, second and third graph show the performance of shallow, intermediate and deep network model respectively. The performance is measured in terms of accuracy as well as loss.

We used the optimised model to evaluate the classification accuracy of DIH micrograph of various cell lines. The performance is as shown in the confusion matrix of figure 4.

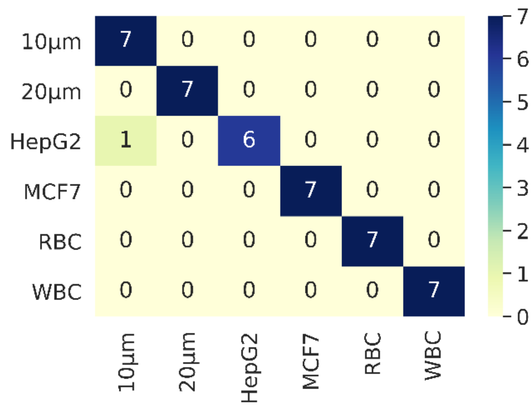

Fig 4. The confusion matrix, showing classification accuracy of the optimized CNN model across all cell lines.

We have evaluated our model with the standard support vector machine (SVM). The comparison shows ~97% accuracy for CNN and approximately about 71% for SVM.

The performance of CNN is better than the analytical model as described by Roy et al. [7], which showed a classification accuracy of about 95%.

IV. Conclusion

We have developed and optimized a convolutional neural network architecture for auto characterization of digital inline holography micrograph. The results from the optimized model shows an accuracy of ~ 97%. The performance is better than our previous analytical model as described by Roy et al. Since the DIH system is a very compact and low-cost setup, therefore the system together with the automated characterization modality may be useful for developing a portable telemedicine device for resource limited settings of the world.

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