Research Journal of Computer Systems and Engineering (RJCSE)
Volume 3 Issue 2 (2022) | Pages: 39 – 45 | e-ISSN: 2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.54

Prediction Analysis of Urinary Tract Infection through Transfer Learning Techniques

Received: 12 October 2022; Revised: 07 December 2022; Accepted: 22 December 2022

Dr. Anasica S
MGM Department, The Free University of Berlin, Germany
anasica.s@ubingec.ac.in

Prof. Dipannita Mondal
Assistant Professor Artificial Intelligence and Data Science Department,
Dr. D.Y.Patil College of Engineering and Innovation, Talegaon, 410507
ddmondal2684@gmail.com

Abstract

The occurrence and presence of a urinary infection in the urinary tract can lead to the damage of normal functioning of the human body including the renal body parts. This may further have a larger impact on the health of an individual and might increase the adversity of his life including the healthcare costs. Hence, its detection at the right stage is important. To achieve the target of this purpose; the proposed research paper aims to focus on detecting the same through the usage of transfer learning models. For this reason the author of the research paper deploys the model in two stages wherein the first stage includes the clinical visit of the patient to the doctor so that manual inspection of the infection can take place and the second stage of the research includes the prediction of the infection through the usage and implementation of transfer learning models and respective algorithms. Four transfer learning based algorithms namely; ResNetV2, MobileNet, Inception and VGGNet are used as transfer learning models and the respective prediction for the presence of urinary infection in the tract is observed.

Keywords

CT-Scan, deep learning, transfer learning, urinary infection, transfer learning, VGG-16

1. Introduction

The occurrence of any form of infection in the urinary tract is observed to be a commonly occurring disease and is witnessed to be present in largely female bodies. Approximate calculations of 30percent of women experience this form of infection with subsequent severity being on an increase with passage of time. Hence, an appropriate form of antibiotic therapy is required so that the disease and the infection can be diagnosed at the right time and therefore be cured. Multiple symptoms are also observed with respect to the same which includes an abrupt failure and damage of renal organs followed by failure of pyelonephritis. In addition to this; the healthcare costs and screening costs of the same are equally challenging for the patients due to the elevated expense the infection brings along with it. The infection in the urinary tract might also spread other diseases and infections such as that of sporadic and recurrent infections wherein the role of the bacteria plays a major part. The bacteria in this case begin to multiply it in getting in contact to various other bacteria which are already present in the tract. The tendency of such bacteria begins to increase and spread with passage of time. This also leads to multiple intestinal infections wherein a pathogen is responsible for the spreading of the disease with respect to different hosts present in the bacteria. Therefore in order to prevent further contamination and spread of the disease; the detection and diagnosis of the infection is mandatory.

Deep Learning, artificial intelligence and transfer learning on the other hand are recently adopted methods which are primarily used in order to diagnose the occurrence of such disease in the human body. With advancements being made in the respective fields a detailed and technical examination of the patient along with its symptoms takes place. In addition to technical examinations; clinical examinations and manual checking of the patient also takes place. At times laboratory findings are taken into consideration so as to reach to a conclusion. This process of treatment is quite a major and long detailed procedure wherein each and every symptom of the individual in the human body is checked and verified. On the basis of the reports thus generated; further treatments and recommendations take place. Various AI, DL and Transfer Learning based models are used to fulfil the purpose of the same. Commonly used algorithms include the implementation of random forest, decision trees, support vector machine, neural networks, VGGNet, ResNet, Inception etc. On the basis of the algorithms used; a prediction mechanism is therefore built and various tools are further incorporated in the same. Apart from this; the concept of taking patient data on various cloud platforms is also majorly adopted in various research areas; wherein the patient gets the advantage of uploading his sensitive data on cloud based platform and further chose his doctor on the basis of his preference. The doctor further gets to advice the patient with respect to the medicines and observed symptoms. The patient data is further securely maintained and monitored on the cloud. The patient also has the advantage to download the data and his files as and when necessary.

As per the literature survey thus conducted in the sections further; it has also been observed that there are certain and specific factors which are also responsible in order to provoke the evolution of the infection in the human body. The primary categories of such risk factors majorly includes health related factors and psychiatric factors. A detailed explanation of the same can be explained as:

- Physical related health factors: when it comes to various infections with respect to individuals; they tend to forget the symptoms they might be experiencing from the very beginning. Such symptoms includes the occurrence of orthopaedic, respiratory, urology/renal, gastrointestinal, and cardiology conditions. With the presence of such symptoms; a huge amount of burden with respect to human health is observed on the urinary tracts wherein the female body begins to worsen and their health takes a toll on the same. Apart from this; the infections might even spread to various internal intestines and may result in intestinal damage; hip replacement, chest infections etc.
- Psychiatric related factors: apart from the physical related issues; there are various other factors related to the mental health and well-being of an individual. Such factors are included in this category wherein the behaviour of the individual is observed and the risk of admitting the patient in the hospital is taken

2. Related Works

A subset of machine learning known as "deep learning" uses a multi-layered approach to help perform better classification tasks, such as finding the relationship between disease-related symptoms and outcomes, clustering patients based on similar characteristics and severity, and identifying anomalies and irregularities in medical images. The additional advantage of deep learning over other forms of machine learning is that it requires far less human involvement in decision-making. The layers of a neural network learn from vast amounts of data in a manner akin to that of the human brain. An investigation of deep learning techniques previously applied to renal object detection is summarized in this section.

The term "image pre-processing" refers to a set of procedures used on photos to enhance its visual quality and fix any possible defects or disruptions. There will be some speckle noise in the images produced since medical imaging requires complex technology and a variety of ray types. An overview of studies that have highlighted the importance of image preprocessing methods is provided in this section.

To raise the quality of the photos, several stages of pre-processing might be used. [1] have suggested a three-step pretreatment methodology that can be applied prior to the segmentation process. The effectiveness of every preprocessing step was assessed using the Sensitivity parameter. It was discovered that the final output photos had 95% sensitivity. The various pre-processing methods were applied to the CT scan images of thirty patients. The three thresholding techniques have been used to remove unwanted regions based on size, location, and intensity. This method's limited source data for model construction is a downside. This study clarifies the various methods that can be used to remove undesired regions.

Intensity Histogram Analysis was utilized to successfully extract 19 distinct GLCM features through feature extraction [2].The source photos for the model building were obtained through ultrasound imaging. Prior to identifying the region of interest, the input US images were cropped, and the urinary contours were identified. Using ultrasound images from this investigation, four groups were created according to the type of renal failure. The results of this stage can be utilized to efficiently determine whether urinary infections are present in medical photos by using the feature extraction method, which clearly shows the different features in the source images.

As a result, the significance of the different pre-processing steps that must be completed before categorization was made clear in this part by examining past research in the Image Pre-processing field. Three main pre-processing techniques are utilized: picture normalization, image scaling, and feature extraction. Thus, in order to improve image quality and facilitate the modeling process, this research uses image scaling and image normalization.

The section on Related Work explored the different ways that have been used to determine the existence of urinary infections using deep learning techniques, along with the benefits and drawbacks of each research design. The infection dataset was modeled using deep learning approaches, as determined by the review. The fundamental pre-processing methods that ought to be used when utilizing deep learning for image classification were also determined, and the general direction of the study was established following this rigorous evaluation and contrast of various approaches in earlier studies. It was noted that the four deep learning networks—ResNet, VGG16, MobileNet, and InceptionNet—were never combined to perform urinary infection detection in any of the aforementioned studies, and that there was no useful comparison of these techniques' classification performance for urinary infection detection. This study fills this gap by offering a thorough analysis of these networks' suitability for infection detection from CT scan pictures.

3. Methodologies Used

A Image Augmentation

The process of adding altered versions of already-existing photographs to a dataset in order to artificially increase its size is known as "image augmentation" [3]. Robust models will be constructed by training deep learning networks on larger datasets, which will also solve the issue of over fitting or model generalization. Several augmentation techniques, including zooming, rotation, and flipping, have been applied to the current photos in the dataset using the ImageDataGenerator function of the Keras API. Since the augmentation takes place during runtime, freshly created data won't be locally preserved in the source folder holding the original dataset. Table 1 displays the various augmentation settings as well as the precise values supplied. The zoom_range describes the amount to which an image is randomly zoomed. The rotation in degrees for an image is indicated by the rotation_range parameter. The flip parameters, both horizontal and vertical, indicate how much an image is flipped.

Table 1: Augmentation Parameters

Parameters	Values
zoom_range	0.3
rotation_range	14
horizontal_flip	15
vertical_flip	12

B Algorithms Used

This section explains the many models that will be applied in order to accomplish the research goal of classifying urinary infection using CT scan pictures. The CRISP-DM approach's modeling phase entails three distinct tasks, including model selection, test design, and model construction. The following are the many models used in the study:

- MobileNet: According to [4], MobileNet is a convolutional neural network designed for mobile applications that specializes in deep learning. The primary distinction between the MobileNet network and other neural networks is that, when compared to other networks of the same depth, it uses less parameter. Depth wise separable convolutions, which comprise two distinct operations—the depth-wise convolution and the point wise convolution—are a unique kind of convolutions used by MobileNet. MoblieNet was created with the goal of efficiently boosting accuracy while taking into account the constrained resources seen in embedded or mobile applications. The depth-wise convolution filter performs a single convolution on each channel, and the point convolution filter combines the output of the depth-wise filters in a linear fashion. Both the model's size and computational cost drastically drop as a result of this factorization. There are two hyper-parameters in the network: the width multiplier and the resolution multiplier. The uniform reduction of the network's size is the width multiplier's primary purpose. The photos used in the dataset had their resolution decreased using the Resolution multiplier. In the baseline MobileNet neural network, there are 28 layers, excluding the depth-wise and point-wise convolution layers.

- VGGNet: Expanded as "Very Deep Convolutional Networks for Large-Scale Image Recognition," VGGNet is a convolutional neural network. When trained on the ImageNet dataset, the VGGNet yielded an accuracy of 92.7% [5]. Over 14 million photos from thousands of different classes can be found in the ImageNet dataset. By replacing the number of kernel-sized filters with smaller kernel-sized filters, the high performance is attained. The VGGNet dataset requires 224*224 resolutions for its input photos. The length of time required for model training is the main disadvantage of the VGGNet. The VGG takes up more than 533 MB of space because of the quantity of connected nodes and the depth of the layers. The VGG network comes in two categories: VGG16 and VGG19, which correspond to the number of convolutional layers in the model. In comparison, the convolutional filters used in VGG16 are rather modest. The VGG16 network consists of three fully linked layers and thirteen convolutional layers. The rectified linear unit, or ReLU, activation function is used by VGGNet. If the input is positive, this function will propagate it; if not, the output will be zero.
- InceptionNet: When trained on the ImageNet dataset, the image recognition model InceptionNet yields an accuracy of more than 78.1% [6]. The model's building pieces include fully connected layers, dropout layers, convolutions, concerts, average pooling layers, and other symmetric and asymmetric components. The Batch Normalization layers are heavily utilized by the model to activate the inputs. Through the standardization of inputs to the model's layers, these batch normalization layers help to stabilize the learning process and reduce the number of epochs. InceptionNet, which also performs maximum pooling, starts with an input that has three filter sizes [7]. A max pooling layer's primary role is to determine which value in a feature map is the largest. Using clever factorization techniques improves the efficiency of the neural network's convolutions [8]. representation
- ResNeT50V: ResNet50 is a residual neural network made up of stacking multiple residual blocks on top of one another to form a convolutional neural network with 50 layers [9, 10]. The purpose of the residual networks was to solve the issue of vanishing gradients. A convolutional neural network's capacity to identify and represent picture features grows with the number of layers in the network. Increasing the number of layers has the disadvantage that, after a while, saturation of the accuracy levels could occur, leading to degeneration. The term "vanishing gradient problem" refers to this decline. The idea of skip connections improves accuracy by using residual blocks. An additional route for the gradients to pass through is offered by the skip connections. Additionally, they give the model the ability to learn an identity function [11]. A three-layer block designed especially to get over the bottleneck that gave rise to the ResNetV50 architecture. When compared to VGGNet, ResNet uses less filters overall.

4. Design Specifications

A Architectural Flow

The techniques, architecture, and framework supporting the implementation are identified and presented in this part together with the related requirements. Figure 1 shows the flow of the project design process. The photos that will be used to model the data are first taken from the github repository and then go through a variety of preprocessing steps to improve their quality. The implementation of the research is divided into two stages. In the first phase, source photos are used for model building without any trimming. Phase 2 employs a different workflow in which the dataset's original photos are cropped to concentrate on the urinary infections, the target location. Pre-processing tasks including image normalization and scaling are carried out in this study. Next, in order to address the over-fitting issue that arose during the modeling process, the pre-processed photos were enhanced. The four deep learning networks—MobileNet, ResNet, VGGNet, and InceptionNet—are then trained on the dataset in question to carry out the classification. Each of these networks' classification performance is evaluated using various assessment criteria, including accuracy, precision, and recall.Github provided the dataset that will be used in the modelling process. Python was the programming language of choice for creating the deep neural network models. Deep Learning network modelling and development demand a significant amount of processing power. A web-based Integrated Development Environment called Google Collaboratory was thus used to frame the Python code base.

Google Collab makes it possible to connect to powerful GPUs via the cloud, making it possible to model even the most complicated neural networks with ease. An NVIDIA GPU with 27.3 GB of RAM available was used in this study's model construction. A high-level neural network library

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 3 Issue 2 (2022) | Pages: 39 – 45 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.54

called Keras has been employed in the study to facilitate easy prototyping and processing. Tensorflow framework has also been utilised in addition to Keras. The dataset was uploaded to Google Drive in order to be accessed through Google Collaboratory [12].

B Transfer Learning Models

Transfer learning is the process through which knowledge or information gained from addressing one problem may be used to solve another that is similar in nature [13]. The present study utilizes four neural networks to construct models, all of which apply the transfer learning technique. The ImageNet dataset is used to pre-train each of the four networks under consideration: MobileNet, VGGNet, ResNet, and InceptionNet. Rather than creating every layer in these networks from the ground up, the Keras [14]. Applications package provided the foundation model for each network. The model's layers are kept in order to preserve the features that were extracted in earlier iterations. Then, additional layers are added to the current network to enable the conversion of old information into new predictions and the model is trained on the urinary images dataset.

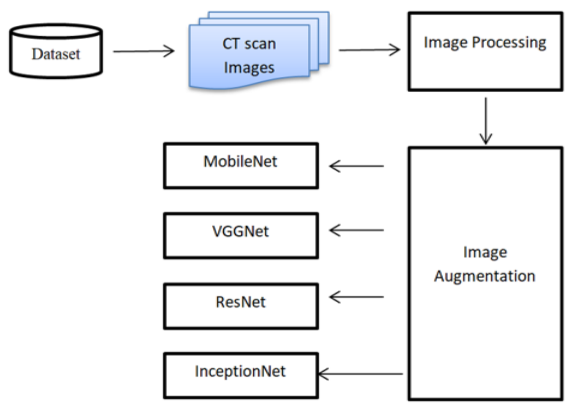

Figure 1: Architectural Flow

Table 2 displays the collection of new layers that were added to the four pre-trained models. The newly developed models are then trained using the fresh dataset in order to assess test accuracy and validity.

Table 2: Collection of layers

Layer	Parameter
DropOut	0.4
Normalization	NIL
Dense	1028
DropOut	0.3
Normalization	NIL
Dense	1024

5. Results

An overview of the many metrics that may be used to evaluate the neural networks' classification performance during the modeling process is given in this section. According to [15] there are three criteria used in the evaluation process: precision, recall, and accuracy. A statistic called precision quantifies a model's capacity to identify a specific sample as positive. The ratio of correctly classified positive samples to the total number of samples that have been declared positive is used to compute precision. To put it briefly, precision offers an indication of how consistently the model classifies a given sample as positive. Recall is a statistic that simply considers how positive samples are classified; it gives no regard whatsoever to negative samples. The number of samples that are positive and appropriately identified as positive, divided by the total number of positive samples, is the definition of recall. Recall values that are high suggest that there have been more positive samples found. One measure that is used to characterize the classification performance across all classes is accuracy. By dividing the number of accurate forecasts by the total number of predictions, accuracy can be calculated. The Keras built-in metrics attribute has been used to calculate the precision, recall, and accuracy for each of the tests listed below.An iterative method determines the number of epochs in this study. The number of epochs was initially set to 10 by default when each model was run because a random number has to be supplied to this attribute to create the model. It is seen that, in line with expectations, validation accuracy rises with each epoch based on the training accuracy data. There will come a time when this accuracy rise stops, which we might refer to as the saturation point. It is observed that the saturation point for models constructed with the cropped dataset happens after the sixth epoch, and for models constructed with the original picture dataset, it happens after the tenth epoch.

Case Study1: Implementation of the VGGNet model

In this experiment, the base layers of the VGG16 neural network model are rendered unattainable and accessed via the Keras API. The basic VGG16 is enhanced with a new set of layers, as explained in previous sections, and the model is then assembled to generate results based on accuracy, precision, and recall. For the original and cropped datasets, the number of epochs is set at 10 and 6, respectively. Table 3 presents the findings from Case Study 1. It can be shown that accuracy, precision, and recall values all rise with increasing epochs for both cropped and unmodified datasets. As can be observed, compared to the results of the model produced using the unmodified dataset, the accuracy, precision, and recall of the VGG model built using the cropped dataset have risen by 26%, 20%, and 20%, respectively. Up to epoch 9, the accuracy values of the VGG Model constructed using the original dataset grow steadily with epoch increase. After that, a decline in accuracy is seen.

Case Study2: Implementation of the ResNet model

Two versions of the model are built for the unmodified and cropped datasets, respectively, using the ResNet50 model imported through the Keras library. The results of the model building process are displayed in Table 3, where it is observed that the number of epochs taken for the unmodified dataset before the saturation of training accuracy is more than the number of epochs required for the model built on the cropped dataset. The unmodified dataset was used to build the ResNet model, and the accuracy, precision, and recall values all fall within 0.57 and 0.60. Cropping the photos in the original dataset boosts accuracy by 23.2%, precision by 34%, and recall by 21.4%. This quick improvement in performance based on all three metrics suggests that cropping the photographs was a successful operation to improve model performance.

Case Study3: Implementation of the Inception Net model

Additional layers are added to the base InceptionNet model, which may be accessed using the Keras API. InceptionNet V3 was the version of InceptionNet utilized in this experiment. Table 3 displays the findings from the two models that were constructed using the urinary infection dataset that has been cropped and left unaltered. The cropped dataset is used to build the InceptionNet model, which yields the best accuracy of any model constructed in this study—0.86%. For the same dataset, the models with the highest precision and recall values in this study—0.866 and 0.831—are also found in this research. When the model constructed using the original dataset is compared to the model constructed using the changed dataset, the increases in accuracy, precision, and recall are as follows: 29.5%, 32.90%, and 19.3%.

Case Study4: Implementation of the Mobile Net model

The MobileNetV2 serves as the foundation model for this experiment and is a lightweight version of the MobileNet model. The table 3 displays the variances in Validation Accuracy, Validation Precision, and Validation Recall for the models constructed for the original and cropped dataset. Table 3 illustrates that the two model versions mentioned above have a set number of epochs of 10 and 6, respectively. Accuracy, precision, and recall have all increased by the following percentages as a result of the cropping process: 28.4%, 31.95%, and 20.3%, respectively.

Table 3: Accuracy Table

Model	Accuracy	Precision	Recall
VGGNet	0.83	0.81	0.8
ResNet	0.86	0.87	0.85
InceptionNet	0.88	0.87	0.85
MobileNet	0.9	0.92	0.9

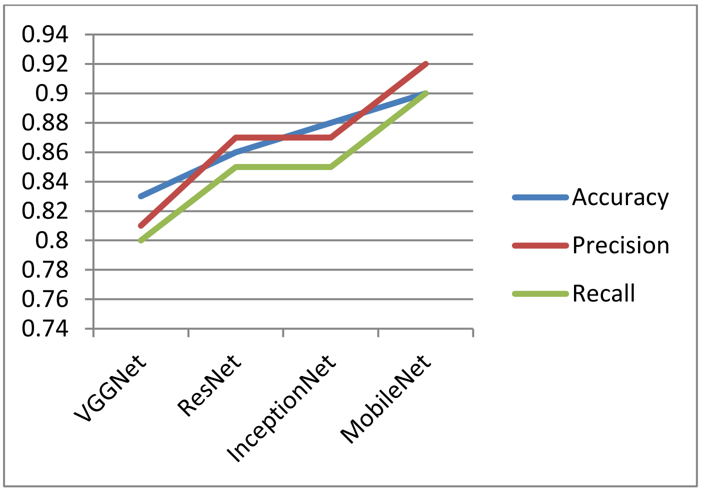

Figure 2: Comparative Analysis

6.Conclusions and Future Works

The development and maintenance of a urinary tract infection can cause harm to the body's regular functioning, particularly the renal system. This might also have a greater effect on a person's health and raise his life's challenges, including the expense of medical care. Therefore, it's critical to discover it early. The suggested research study intends to concentrate on detecting the same through the use of transfer learning models in order to fulfil this purpose. Because of this, the research paper's author deploys the model in two stages: the first involves the patient visiting the doctor for a clinical visit so that an infection can be manually inspected, and the second stage involves using transfer learning models and corresponding algorithms to predict the infection. As transfer learning models, four algorithms—ResNetV2, MobileNet, Inception, and VGGNet—are employed, and the corresponding prediction for the existence of a urinary tract infection is noted

References

[1] Medina, M. & Castillo-Pino, E. An introduction to the epidemiology and burden of urinary tract infections. Ther Adv Urol. 11, 1756287219832172 (2019)

[2] Klein, R. D. & Hultgren, S. J. Urinary tract infections: Microbial pathogenesis, host-pathogen interactions and new treatment strategies. Nat. Rev. Mic robiol. 18, 211–226 (2020)

[3] Bandari, B., Sindgikar, S. P., Kumar, S. S., Vijaya, M. S. & Shankar, R. Renal scarring following urinary tract infections in children. Sudan J. Paediatr. 19, 25–30 (2019)

[4] Ciani, O., Grassi, D. & Tarricone, R. An economic perspective on urinary tract infection: The "costs of resignation". Clin Drug Investig. 33, 255–261 (2013)

[5] Renard, J. et al. Recurrent lower urinary tract infections have a detrimental effect on patient quality of life: A prospective, observational study. Infect. Dis. Ther. 4, 125–135 (2015)

[6] Kodner, C. M. & Thomas Gupton, E. K. Recurrent urinary tract infections in women: Diagnosis and management. Am. Fam. Physician. 82, 638–643 (2010).

[7] Wang, M. C. et al. Different roles of host and bacterial factors in Escherichia coli extra-intestinal infections. Clin. Microbiol. Infect. 15, 372–379 (2009)

[8] Ahuja, A. S. The impact of artificial intelligence in medicine on the future role of the physician. PeerJ 7, e7702 (2019)

[9] Burton, R. J., Albur, M., Eberl, M. & Cuff, S. M. Using artificial intelligence to reduce diagnostic workload without compromising detection of urinary tract infections. BMC Med. Inform. Decis. Mak. 19, 171 (2019)

[10] Ozkan, I. A., Koklu, M. & Sert, I. U. Diagnosis of urinary tract infection based on artificial intelligence methods. Comput Methods Programs Biomed. 166, 51–59 (2018)

[11] Mancini, A. et al. Machine learning models predicting multidrug resistant urinary tract infections using "DsaaS". BMC Bioinform. 21(Suppl 10), 347 (2020)

[12] Dason, S., Dason, J. T. & Kapoor, A. Guidelines for the diagnosis and management of recurrent urinary tract infection in women. Can. Urol. Assoc. J. 5, 316–322 (2011)

[13] Park, J. I., Bliss, D. Z., Chi, C. L., Delaney, C. W. & Westra, B. L. Knowledge discovery with machine learning for hospital-acquired catheter-associated urinary tract infections. Comput. Inform. Nurs. 38, 28–35 (2020)

[14] Sherazi, S. W. A., Jeong, Y. J., Jae, M. H., Bae, J. W. & Lee, J. Y. A machine learning-based 1-year mortality prediction model after hospital discharge for clinical patients with acute coronary syndrome. Health Inform. J. 26, 1289–1304 (2020)

[15] Gadalla, A. A. H. et al. Identification of clinical and urine biomarkers for uncomplicated urinary tract infection using machine learning algorithms. Sci. Rep. 9, 19694 (2019).