

Urinary Tract Infection Bacteria Classification: Artificial Intelligence-based Medical Application

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Abstract—Urinary tract infection (UTI) is a type of health disorder, an infection in the urinary glands mainly caused by bacteria. Currently, conventional early detection methods that have been established involve rapid dipstick strip test and urine culture analysis, which have suboptimal accuracy and effectiveness. Several retrospective studies regarding UTI bacteria classification have shown promising results, but still have limitations regarding prediction accuracy and technical simplicity. This study aims to implement a method based on artificial intelligence (AI) in classifying images of bacteria that causes UTIs. Eight artificial intelligence methods based on deep neural networks were used in the study; the models were evaluated and compared based on the prediction's effectiveness and accuracy. This study also seeks to create the easiest method of classifying bacteria causing UTIs using a computer-based application with the best obtained AI-based model. The best training results using an intelligent approach placed DenseNet201 as the method with the highest accuracy (83.99%). Then, the output model was used as a knowledge reference for the designed computer-based application. Real-time prediction results will appear in the application window.

Keywords—Artificial Intelligence; Computer-based Application; Prediction; Rinary Tract Infection.

I. INTRODUCTION

Urinary tract infection (UTI) is one of the infections caused by these two bacteria, including Gram-negative and Gram-positive bacteria, and certain fungi, colonizing in excess and the most common to be found in medical practices [1]. UTIs affect 150 million people worldwide each year [2]. This illness is classified as either uncomplicated or severe UTI.

Uncomplicated UTIs typically occur in healthy individuals with no structural or neurological abnormalities of the urinary system. Uncomplicated urinary tract infections (UTIs) are classified as lower UTIs (cystitis) and higher UTIs (pyelonephritis). This category frequently contains *Staphylococcus saprophyticus*, *Enterococcus faecalis*, and *Streptococcus agalactiae* (group B *Streptococcus*, GBS) [3].

Meanwhile, a complicated urinary tract infection (UTI) is defined as one that is associated with factors that impair the urinary tract or host defines, such as urinary obstruction, urinary retention caused by neurologic disease, immunosuppression, renal failure, kidney transplantation, pregnancy, or the presence of foreign bodies such as stones,

catheters, or bladders, and additional drainage devices [4]. Urinary tract infections caused by catheters are the most frequent, accounting for 70% - 80% of cases [5], which have been linked to worse patient outcomes. While complicated UTIs are frequently discovered due to *E. coli* infection, these *Enterococcus faecium*, *Proteus spp.*, and *Staphylococcus saprophyticus* bacteria are also detected, albeit infrequently.

Enterococcus faecium and *Staphylococcus saprophyticus* are salt-positive bacteria typically found in the human flora but can cause various health concerns when present in excessive amounts [6]–[8]. Both are critical for human health since they are the primary cause of healthcare-associated infections.

Enterococcus faecium also may cause urinary tract infections (UTIs) [9]–[11], endocarditis, and bacteremia. Enterococci can exist either as single cocci or pairs, in chains or clusters [12]. They are facultative anaerobes with chemo-organotrophic metabolism and homofermentative metabolism, with lactic acid as the primary end product of carbohydrate fermentation. Thus, they can survive in adverse circumstances, making them well-suited to healthcare settings.

S. saprophyticus, on the other hand, colonizes the perineum, rectum, urethra, cervix, and human digestive tract. These bacteria are often responsible for urinary tract infections. *S. saprophyticus* colonies are frequently yellow in color [6], [13], [14]. The tolerance of *S. saprophyticus* to Novobiocin distinguishes it from other coagulase-negative staphylococci. *S. saprophyticus*, like other pathogenic organisms, produces ammonia via urease. However, unlike many of these organisms, it cannot reduce nitrate, making the nitrate culture test unsuitable for detecting these bacteria.

In other words, several bacteria that are the leading cause of urinary infections include *E. faecium*, *Proteus spp.*, and *S. saprophyticus*. These bacteria can be recognized as biomarkers for UTIs. Currently, conventional early detection methods that have been established involve rapid dipstick strip tests and urine culture analysis, which have suboptimal accuracy and effectiveness. The process of early detection to identify urinary infections has been using the laboratory test method. This conventional method tends to take a relatively long time.



In recent years, medical-based applications using artificial intelligence approaches have been developed to support preventive measures and disease detection in the health sector. The implementation of artificial intelligence (AI) in supporting the medical world can be in the form of early detection of diseases based on images of organs [15]–[17] and wave patterns of vital organs found in the human body [18]–[21]. More precisely, AI's use in the medical profession has advanced significantly in recent years. AI has been developed to identify a variety of medical problems, including low ejection fraction (EF) in ECG signals [22]–[24], dental restoration detection [25], suggestions on dental caries [26], feedback on facial orthognathic assistance to dentists [27], providing medical aid program suggestion [28], and identification of polyps [29], [30]. Additionally, medical professionals can use artificial intelligence to identify proper squat form for physical therapists [31], improve the accuracy of skeletal age assessments, speed up radiologists' interpretation times [32], pre-assess priority care digitally [33], and provide recommendations in physician diagnosis [34], [35].

Applications of artificial intelligence in disease detection include pneumonia fast testing [36], breast cancer detection [37]–[41], gastric cancer identification [42], tumor detection [43]–[45], epilepsy detection [20], [46]–[48], malaria detection [49], and blood cancer detection [50]. The artificial intelligence approach is carried out using either a window-based application [51]–[53], a mobile phone [54]–[56], or a centralized computer application [57], [58].

Applying artificial intelligence in practical topics has experienced rapid development [59]–[61]. Artificial intelligence, apart from being used in the medical world, can also be used to support field problems such as waste processing [62]–[64], vehicle number plate detection [65]–[67], and human emotion detection [68]–[70].

The research contribution of this work is to find the best method by comparing some image classifier methods for bacteria causing urinary infections using an artificial intelligence approach. The best model with the highest accuracy results was then used as a reference model for making computer-based software applications. This software is representative of urinary bacterial infection detection using bacterial images captured by a microscope camera. This computer-based software will display a complete and detailed urinary infection prediction.

II. MATERIALS AND METHODS

A. Materials

This study used a dataset from the Digital Images of Bacterial Species (DIBaS) [71]. It consists of images of bacteria with several data classes. Then, the dataset was divided into two classes: urinary and non-urinary infections.

Table I shows the bacterial species distribution in the two classes. Species of bacteria included in the data class of non-urinary infection were *Actinomyces israeli*, *Candida albicans*, *Clostridium perfringens*, *Escherichia coli*, *Lactobacillus*, *Listeria monocytogenes*, *Porfyromonas gingivalis*, *Pseudomonas aeruginosa*, and *Veionella*.

Meanwhile, *E. faecium*, *Proteus*, and *S. saprophyticus* were categorized in the data class of urinary infection.

The dataset contained 394 images of non-urinary bacterial infections and 360 images of urinary bacterial infections. Ideally, image data for each class is divided by 80% for training and 20% for testing. The total epoch of training data was set to 40.

Image augmentation was applied to the images of the urinary infection data subset by modifying the images with horizontal flip, vertical flip, and random rotation. Fig. 1 shows the augmentation example from the original and augmented images.

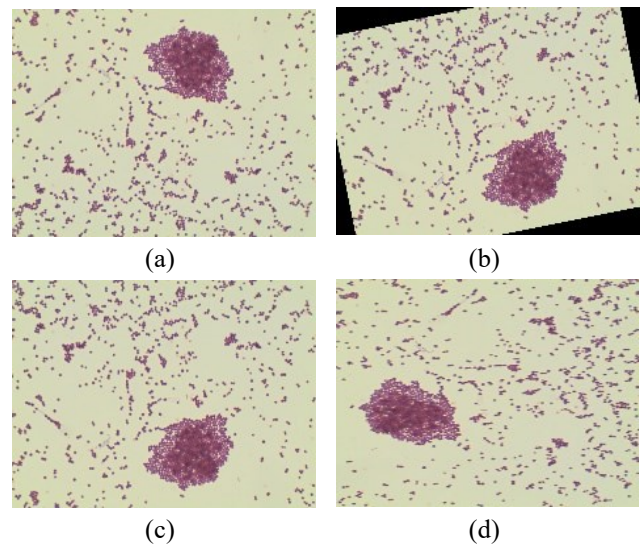


Fig. 1. (a) Original image; (b) Random rotation; (c) Flipped horizontal; (d) Flipped vertical

TABLE I. DISTRIBUTION OF BACTERIA DATABASE

Bacteria Name	Class	Total Images
<i>E. faecium</i>	Urinary Infection	120
<i>Proteus spp.</i>	Urinary Infection	120
<i>S. saprophyticus</i>	Urinary Infection	120
<i>Actinomyces israeli</i>	Non-urinary Infection	23
<i>Candida albicans</i>	Non-urinary Infection	20
<i>Clostridium perfringens</i>	Non-urinary Infection	23
<i>Escherichia coli</i>	Non-urinary Infection	20
<i>Lactobacillus</i>	Non-urinary Infection	220
<i>Listeria monocytogenes</i>	Non-urinary Infection	23
<i>Porfyromonas gingivalis</i>	Non-urinary Infection	23
<i>Pseudomonas aeruginosa</i>	Non-urinary Infection	20
<i>Veionella</i>	Non-urinary Infection	22

B. Intelligence Methods

Identification consists of bacteria classes that infect in this study using an intelligence approach. The intelligence approach is often referred to as the artificial intelligence approach. In this approach, the dataset that has been given image interference is trained to recognize and classify images into two classes. The first class is a urinary infection class and the second class is not a urine infection. The artificial intelligence approach is trained using eight artificial intelligence methods to train image data. These methods

include VGG16 [72], VGG19 [72], Inception V3 [73], Mobile-Net V1 [74], Mobile-Net V2 [74], DenseNet121 [75], DenseNet169 [75], and DenseNet201 [75][76]. Therefore, this intelligence approach requires a lot of training time because the method used is relatively high. Each of these methods has a different number of layers and a different network structure. So, with these variations, it is hoped that there will be an ideal comparison to find out the best intelligence approach method. The step work of the intelligence approach can be seen in Fig. 2. This figure explains that the beginning step after getting image data from an augmented dataset is training the image into eight methods.

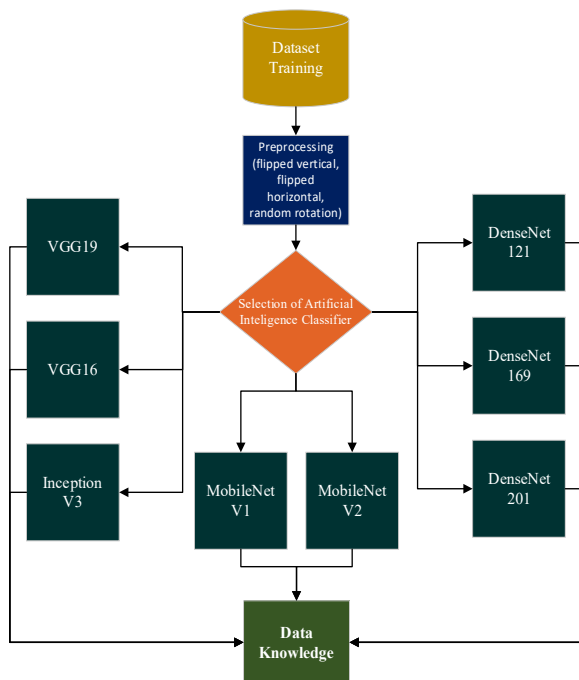


Fig. 2. Intelligence approaches

C. Software Development

The software design uses a visual programming method based on visual studio GUI. Software development is initiated by referencing the artificial intelligence method's final model with the best accuracy. The design of this software has the function of easy and fast detection of bacteria that cause urinary infections. Bacteria detection using the Python platform is integrated with visual studio programming using the C# language. Flow steps for using this software can be seen in Fig. 6. According to Fig. 6, the flow of software usage begins with retrieving bacterial image data stored in the user directory. Users can use various image extensions for bacteria detection. The selected image can immediately detect the content of bacteria that cause urinary tract infections by pressing a button to start detection.

III. RESULTS AND DISCUSSIONS

This study used an artificial intelligence approach to train the image dataset. Image data that several methods have augmented are adjusted based on each class. The parameters used in this image training are conditioned the same for each artificial intelligence method. According to previous research, the equated parameters for each method are learning

rate, epoch, batch size, and image resizing [77]. The difference for each technique lies in the number of layers and the convolution algorithm used. Fig. 3. describes the level of accuracy for each method of artificial intelligence approach. In Fig. 3, it can be seen that each process reaches its optimal accuracy when entering the last epoch.

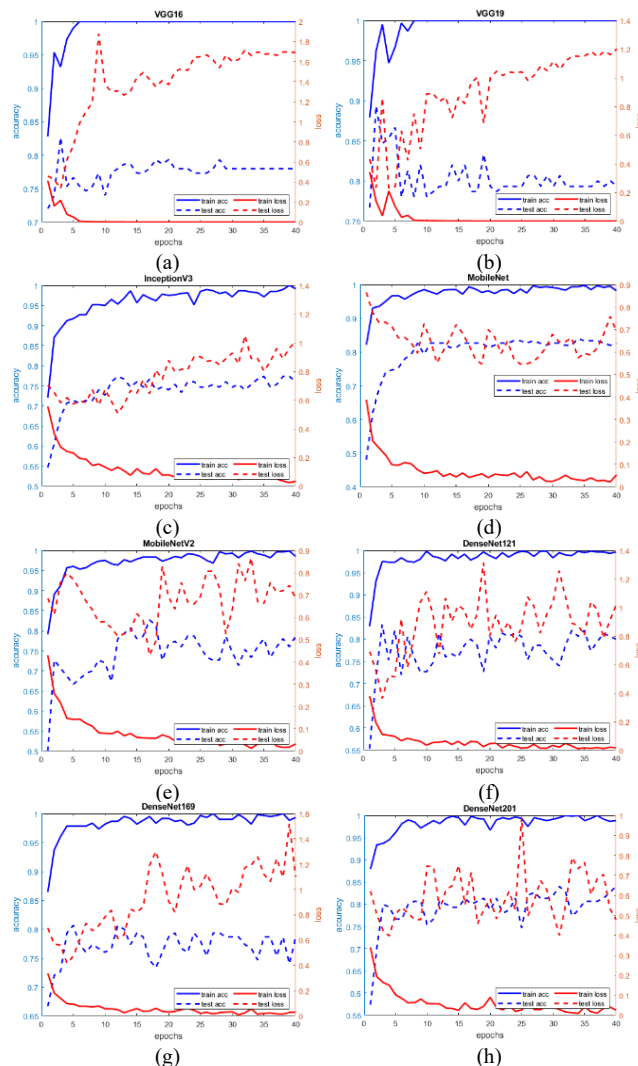


Fig. 3. Accuracy and Loss Results of (a) VGG16; (b) VGG19; (c) Inception V3; (d) MobileNetV1; (e) MobileNetV2; (f) DenseNet121; (g) DenseNet169; (h) DenseNet201

Based on the training results, it can be concluded that the highest accuracy value was obtained using the DenseNet201 method. Other DenseNet methods also have increased accuracy values compared to other approach methods. The graph of accuracy values below indicates that the DenseNet approach's classification level exceeds other methods in terms of accuracy, loss, and layer depth. This result aligns with the CNN method's comparative study [78], [79], which has the highest accuracy output value found in the DenseNet201 method.

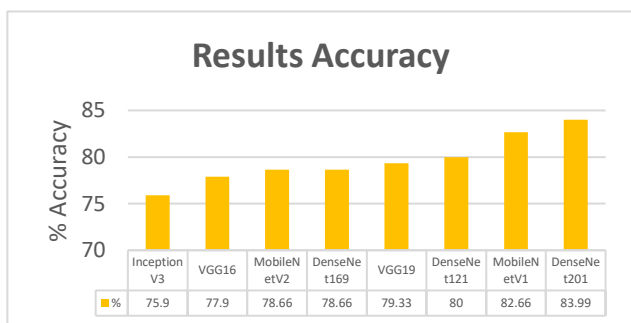
The confusion matrix is used to determine the distribution of data when evaluating the algorithm technique. As indicated in Table II, the confusion matrix in the DenseNet201 model incorporates testing data from 150 images. The confusion matrix data yielded 24 images that

were incorrectly recognized. The test pictures are generated by identifying the detection mistake, as illustrated in Fig. 5.

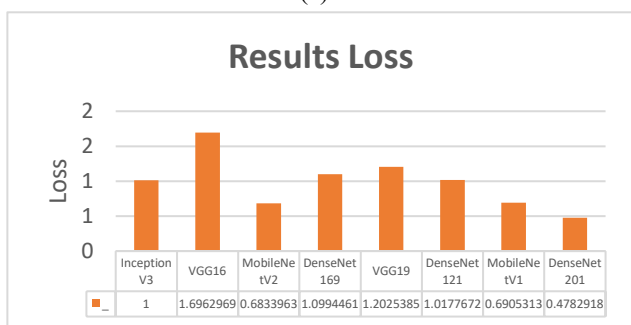
TABLE II. CONFUSION MATRIX DENSENET201

Actual	Urinary	Non-urinary
Urinary	54	24
Non-urinary	0	72

Based on the comparative graph from Fig. 4 (a)-(b), the approach with the lowest accuracy value is InceptionV3, with 75.9%. Furthermore, with the VGG16 model, data retention increased by 2% to 77.9%. The subsequent development of this model, namely VGG19, has increased yield by 1.43% from the previous model to 79.33%. MobileNetV2 and MobileNetV1 using depthwise architecture and pointwise convolution, have a relatively high level of accuracy, with 78.66% and 82.6%, respectively. DenseNet family with a deep layer depth tends to increase the accuracy value based on network depth. DenseNet121, a dense model with the lowest layer, has a classification accuracy value of 80%. However, DenseNet169, which has a layer depth above the previous model, decreased by 1.34% to 78.66%. The last model from Dense Network is DenseNet201, with a deeper layer depth to get the highest accuracy value from all methods. DenseNet201 achieves a final accuracy rate of 83.99% and outperforms all intelligent approach architectures. This study's results align with Albahli's research [78]; the DenseNet network exceeds InceptionV3 in the level of image selection accuracy. The accuracy level of DenseNet201 is the highest according to the comparison of the three DenseNet methods in a recent study [80].



(a)



(b)

Fig. 4. (a) Accuracy Comparison of Each Intelligence Method; (b) Loss

As seen in Fig. 4 (a), different types of artificial intelligence algorithms with the same properties have varying degrees of accuracy. VGG16's accuracy is lower than VGG19's. This accuracy is consistent with Simonyan's

research [72], in which the convolution layer in VGG19 has a more significant number, implying an increase in accuracy. The use of the DenseNet technique yields the same results as the algorithm. DenseNet201, which includes more dense blocks, seems to have a greater accuracy rate, according to DenseNet architecture [75].

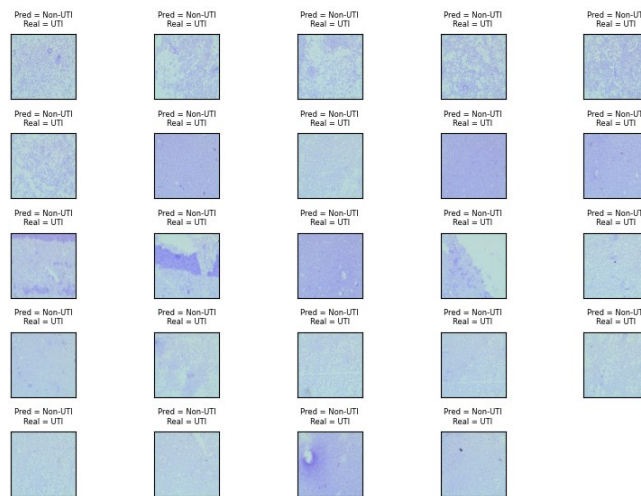


Fig. 5. Misclassification of DenseNet201

In contrast, MobileNet V1 in this study outperforms the MobileNetV2, in terms of accuracy. This result is feasible since MobileNetV2's depthwise separable convolution does not yet have the appropriate support for GPU-based training data. The accuracy of the MobileNet backbone in this investigation is consistent with Howard's research [81].

Each of these artificial intelligence methods has the final output in the form of the highest accuracy model. The model with the highest accuracy is used as a knowledge reference for computer-based applications. Computer-based applications are made using the C# programming language and Visual Studio. Programming with the C# language can bridge the python console interface, which is used as the basis for image classification in computer applications.

Fig. 6 shows that computer-based applications have simple interfaces and prioritize aspects of functionality. In this computer-based application, a computer vision approach is also used to read images from computer directories and resize the original images into images that artificial intelligence models can process.

This image classification process uses the basic idea of classifying images using TensorFlow in Python programming. Python libraries are invoked using the open-source bridge found in basic visual studio programming. This method allows the program to use the base TensorFlow and Keras for the .Net framework platform. This framework supports the integration of various programming languages so that they can be run on computer operating systems.

Based on Fig. 7(a), it can be seen that the GUI display in computer-based applications has a simple, minimalist, and detailed appearance. In the following picture, Fig. 7(b) shows the process of retrieving bacterial image files in the computer storage directory. There are two types of classification: the classification of bacteria that cause urinary infections, as

shown in Fig. 7(c), and the classification of other bacteria that do not cause urinary infections, as in Fig. 7(d).

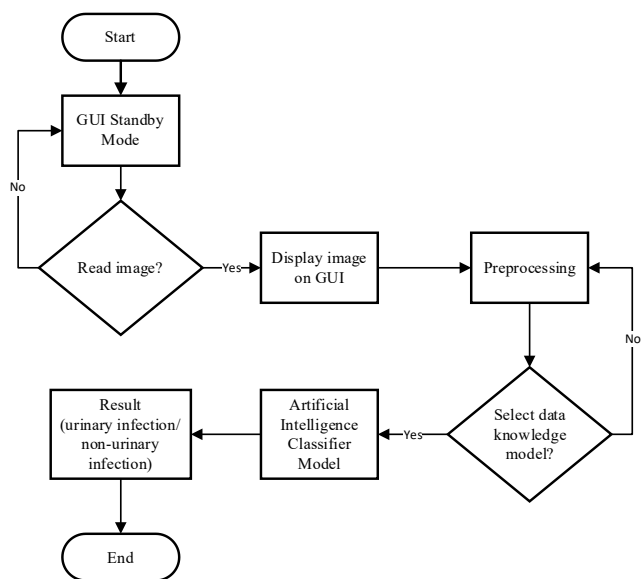


Fig. 6. Computer-based application flowchart

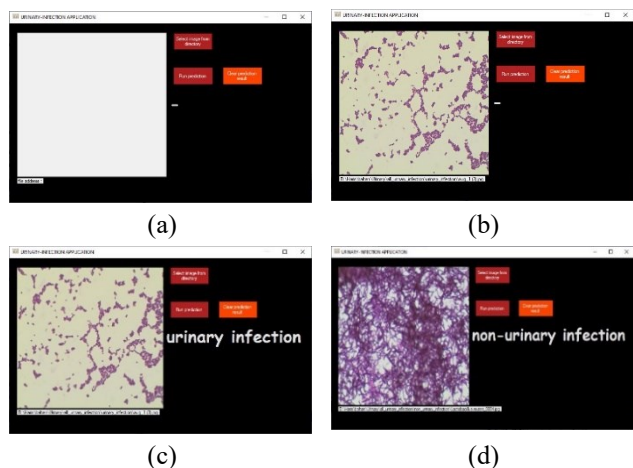


Fig. 7. Graphical User Interface (GUI) urinary infection computer-based software. (a) standby display; (b) importing image form directory; (c) urinary infection prediction; (d) non-urinary infection prediction

IV. CONCLUSION

Eight intelligence approaches have been implemented in this study to find the best method for classifying urinary bacterial infections. Each approach has a different level of accuracy and is influenced by the depth of the network layer. DenseNet201 managed to outperform other approaches with an accuracy rate of 83.99%. The output model from DenseNet201 is used as a reference model in the preparation of computer-based applications. Therefore, at the end of this study, we created a computer software-based method for detecting bacteria that cause urinary infections. Further research into real-time detection utilizing computerized lab samples can be conducted. This computer-based tool is the first step in the early diagnosis of urinary tract infections, providing quick and reliable findings.

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