Utilization of convolutional neural network in image interpretation techniques for detecting kidney disease

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ABSTRACT

This research is conducted with deep learning for kidney stone disease detection including cysts, stones, normal, and tumors using axial computerized tomography (CT) scan images. The author uses augmentation, generative adversarial networks (GANs), original, and synthetic minority over-sampling technique (SMOTE) to classify kidney disease (cyst, stone, normal, and tumor). This study uses the public dataset nazmul0087 and primary data/data from the hospital, using convolutional neural network (CNN) models, namely augmentation, GANs, original, and SMOTE by training and testing. The results of the accuracy value of the training model (dataset nazmul0087) in the detection of kidney cysts, stones, tumors, and normal. The results of augmentation value are 99.93%, GANs 100%, original 100%, and SMOTE 99.93%. In the results of the training model, a very high accuracy value is obtained, with perfect results. The testing model's accuracy value in detecting kidney cysts, stones, tumors, and normal kidney tissue in the original dataset and hospital data. The results of augmentation value are 11.48%, GANs 17.96%, original 21.76%, and SMOTE 20.41%. In the results of the training model, the highest accuracy value is obtained in the original model. For the testing model to automatically diagnose kidney illness and obtain a high accuracy value, which can enhance patient outcomes and save health care costs, we advise using it in conjunction with the original model.

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1. INTRODUCTION

The kidneys are vital organs that keep the body's fluid balance and prevent waste from building up, which helps to regulate blood composition. Artificial intelligence-based systems are beginning to be employed in medical imaging to support wizard evaluations for diagnostic data, including the evaluation of lesions in the urinary tract [1], [2], creating segmentation for medical images [3], anomalies in the abdomen [4], liver cancers [5], cancerous nature of musculoskeletal disorders [6], anomalies in the coronary arteries that affect the calcium score [7], coronary computed tomography angiography (CCTA) interpretation can determine whether stenosis is present [8].

Any age or gender can get kidney disease. The significance of kidney illness early diagnosis. Chronic renal disease can be lethal if treatment is not received [9]. Early diagnosis and treatment of kidney stones, cysts, and hydronephrosis is recommended. The development of chronic kidney disease can be avoided by early detection of kidney stones and tiny tumors [10]. Globally, the number of people with kidney disease is steadily rising, and most nations particularly those in the third world-have a shortage of nephrologists. As a result, many renal patients are unable to get proper care. Regular renal screening for patients should comprise tests using medical imaging equipment [11]. Kidney failure and excruciating pain, can all result from kidney stones [12], [13]. Every year in the United States (US), over 2 million patients visit the emergency room with back pain or colonic disease brought on by kidney stones.

Artificial intelligence is presently being used in medical imaging to diagnose urinary tract problems. Anybody can get kidney disease, regardless of age or gender. One of the most prevalent medical conditions, while the incidence varies by nation, is kidney stone disease [14]. Kidney failure and excruciating pain can result from kidney stones. Hydronephrosis, kidney stones, and cysts should all be identified and treated as soon as possible. Early detection and treatment of kidney stones and tiny tumors can delay the development of chronic renal disease. Both industrialized and developing nations have seen an upsurge in their frequency throughout the last seven years. The significance of renal illness early diagnosis. Chronic renal disease can be lethal for an individual if treatment is not received [15]. Based on the following study, artificial intelligence with deep learning models may be applied in a variety of domains utilizing medical pictures. It can be used to assess anomalies in computerized tomography (CT) scan modalities and significantly help radiologists confirm the diagnosis of abnormalities [16]–[20].

Urolithiasis, or urinary tract stones, can be detected by choosing the appropriate examination method [21]. Urinary tract disorders can be identified by non-contrast computed tomography (NCCT). When diagnosing acute low back pain, NCCT is now the go-to imaging technique. Low-dose NCCT has a sensitivity and specificity of 93.1 and 96.6%, respectively, for detection. Because urolithiasis has enough density to be photographed, NCCT is the gold standard test for urolithiasis detection and characterization, with sensitivity and specificity around 100%. Support vector machine (SVM) and K-nearest neighbor (KNN) are two popular categorization techniques. Artificial intelligence technology is still evolving today, and several studies indicate that deep learning is being utilized more frequently than classical machine learning.

The imbalance in the amount of data may be addressed using a variety of techniques, including feature space augmentation, geometric transformation-based augmentation, and generative adversarial network (GAN)-based augmentation [22]. By adding geometric alterations to the current data, a technique known as geometric data augmentation is used in computer vision and machine learning to expand the variety of a dataset. Through the process of moving picture pixels from their original locations to new locations while maintaining pixel values, the method modifies the geometrical structure of images. These transformations entail changing the data's location, orientation, or scale while keeping all of its original properties. Augmenting geometric data is very helpful for picture data and is frequently used to enhance deep-learning model performance. Rotation, scaling, translation, shearing, flipping, cropping, and zooming are a few typical geometric augmentations.

There are two methods for augmentation of feature space data: undersampling and oversampling. The undersampling strategy aims to provide a more equal distribution across the classes by reducing the amount of samples from the dominant class. Undersampling can assist keep the model from being biased toward the majority class and enhance its capacity to identify the minority class by lowering the quantity of majority class samples. However, undersampling may result in a loss of potentially valuable information, so it should be applied carefully. To get a more evenly distributed distribution among the classes, extra samples from the minority class are produced using the oversampling technique. There are several ways to oversample, but synthetic minority over-sampling technique (SMOTE) is one of the most often employed approaches. SMOTE interpolates between current data points to create synthetic samples for the minority class. This can enhance the model's capacity to learn from the minority class and produce more accurate categorization outcomes. Oversampling should be done with caution, though, since producing an excessive number of synthetic samples might result in overfitting and decreased model generalization.

The term "GAN-based augmentation" describes the process of creating artificial data samples using GANs to supplement an already-existing dataset [23]. This method can assist in balancing the distribution of classes and grow the size of the dataset, which is especially helpful when the initial dataset is small or unbalanced. GAN augmentation has been effective in some fields, including computer vision, natural language processing, and medical imaging. The creation of artificial CT, magnetic resonance imaging (MRI), and x-ray pictures to support illness diagnosis and treatment are a few instances of GAN augmentation in medical imaging.

Radiologists continue to face challenges in diagnosing patients, such as the length of time it takes to analyze reconstruction pictures on CT scan modalities. Determining anomalies from the picture takes time. This research needs to be done because when evaluating CT scan images, there are errors, especially in difficult and small abnormalities. When evaluating CT scan pictures, there is an error, particularly with challenging and minute abnormalities. By eliminating disparities in the evaluation of kidney stone images, automatic detection of urinary tract stones will help address issues with radiological health, including kidney disease detection and prevention, severe pain reduction, and diminished quality of life [12], [13], [24]. This research aimed to create a more balanced dataset in the medical picture of the kidneys by increasing the representation of the minority class so that it is the same as the number of samples in the majority class.

Treating severe lower urinary tract dysfunction (LUTD) may need augmentation. A significant factor leading to the development of urinary tract infections (UTIs), which are linked to a lower chance of transplant survival, is persistent LUTD coupled with residual "bladder valve". While treating KT recipients with LUTD and recurring UTIs may not be simple, doing so is necessary to guarantee long-term graft viability [25], [26].

2. METHOD

Kaggle CT Kidney as shown in Figure 1 is a data set containing clinical images of normal, cysts, tumors, and stones in the kidney. Kaggle data is used in training data, with the number of normal 3284, cyst 2247, tumor 1339, and stone 848. The data is categorized into four categories. In the testing data using primary data in the hospital with the number of normal 540, cyst 602, tumor 494, stone 446. Radiologist experts can assess the diagnosis of kidney abnormalities in the form of normal, cysts, tumors, and stones in the kidney.

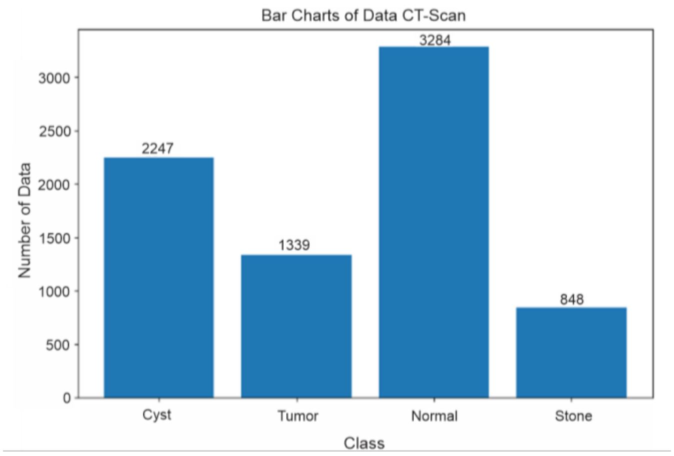


Figure 1. Distribution category of kaggle testing data

To get the greatest performance, some experimental systems were created. The original data (without augmentation) is used in the first scheme to diagnose renal disease. The original data is enhanced utilizing geometric augmentation, GANs augmentation, SMOTE, and original geometric augmentation in the second, third, and fourth schemes.

Previous research related to the detection of kidney stones includes; Deep learning was given, at random, the research model that was applied to CT scan pictures [19]. Using CT scans, the model demonstrated 96.82% accuracy in kidney stone detection using XResnet-50. Small kidney stones may be detected by the model with accuracy. An accuracy of 99.22% was achieved in kidney stone detection using the ExDark19 model [16]. The created automated approach might lessen the likelihood of radiologist mistakes while evaluating kidney stones and assist urologists in doing so manually. Seek to identify an effective method for kidney classification from photos [27]. A novel framework is suggested as a solution to the data imbalance issue. The performance of deep learning models is limited by the unbalanced classes in the data set. Discussed a classification approach using lightweight deep convolutional neural networks (CNN) [28]. The authors propose a modified version: when from the cellular network it achieves higher accuracy, specificity, sensitivity, and F1 score than the traditional cellular network. Discussed a classification approach using lightweight deep CNN. The authors propose a modified version: when using the cellular network, this version achieves higher accuracy, specificity, sensitivity, and F1 score compared to the traditional cellular network.

The kidney disease image dataset used in the study has four classes, namely cysts, normal, stones, and tumors. The training dataset was obtained from public data shown in Figure 2. The testing data distribution category is shown in Figure 3.

The training data from dataset nazmul0087 is displayed on example pictures for each category in Figures 1 and 2, respectively. Clinical metadata is attached to every image in the dataset. Experts in dermatology offer a diagnostic evaluation of every data set. The dataset's high-resolution and high-quality photos make it appropriate for in-depth diagnostic analysis. Researchers frequently utilize nazmul0087 while creating and assessing algorithms for renal disease diagnosis.

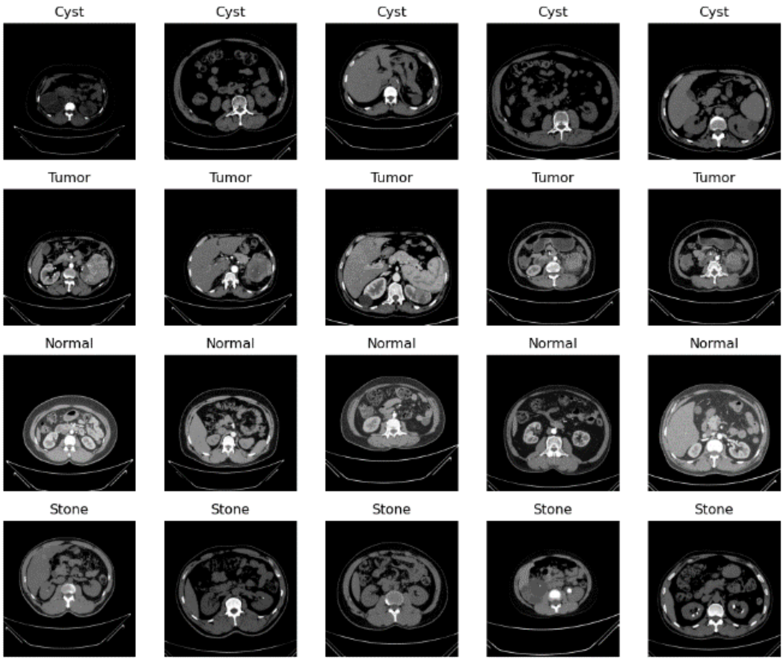


Figure 2. Visualization of sample dataset for each class (training data)

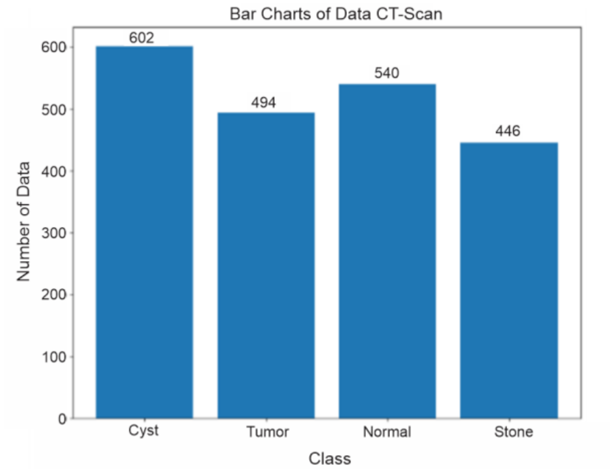


Figure 3. Distribution category of the testing data

The testing data from the hospital's primary data are displayed in Figures 3 and 4. Clinical metadata is attached to every image in the dataset. Experts in dermatology and radiologists offer diagnostic evaluation for every data set. The dataset's high resolution and high-quality photos make it appropriate for in-depth analysis in the diagnosis of renal disease. Stands for GANs which can be used as one of the deep learning methods for data augmentation, particularly in image processing [29]. The architecture of a GANs is an artificial neural network made up of two models called generators and discriminators that play a game to get better at what they do [30].

The oversampling technique known as SMOTE is used to evenly distribute the number of samples in a dataset across the majority and minority classes. Samples from the minority class are chosen at random by SMOTE, which then combines them to produce new synthetic samples. This enhances the ability to classify views on imbalanced datasets. SMOTE, however, tends to add noise and degrade the effectiveness of classification prediction. Thus, by applying k-means clustering to groups of samples and creating synthetic samples only inside clusters with fewer instances of minority classes, K-means SMOTE was created to get around the drawbacks of SMOTE.

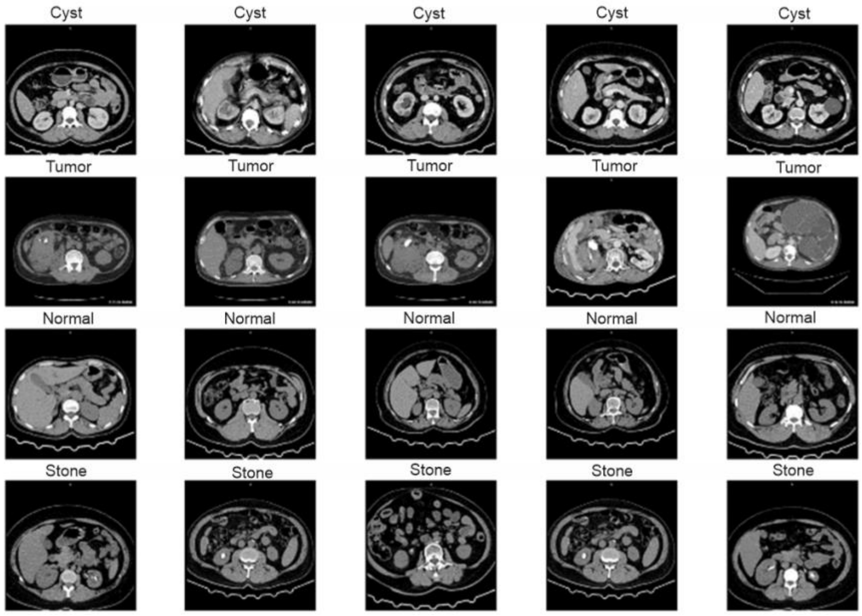


Figure 4. Visualization of sample dataset for each class (testing data)

When completing a new task or when using a deep learning model, transfer learning comes in quite handy. A trained CNN model was employed in this work to classify renal disease. This study used a pre-trained CNN model to classify renal illness. We will use augmentation techniques to add more photographs to categories that have fewer images when we create the model. GANs and SMOTE. The flow of kidney illness detection utilizing original, SMOTE, GANs, and suggested augmentation is depicted in Figure 5. Training data are taken from the nazmul0087 dataset while testing data are taken from the hospital main data.

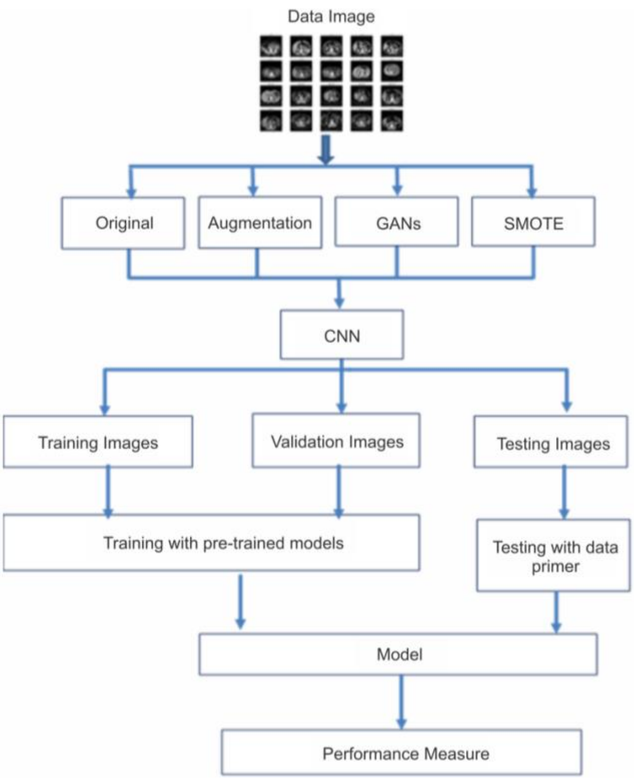


Figure 5. The proposed kidney disease detection

One data augmentation method used in computer image processing, especially in the context of deep learning and pattern recognition, is geometric augmentation. By altering the original image's shape without altering the labels or class information attached to it, geometric augmentation aims to broaden the variety of the training set. By doing this, machine learning models become less reliant on positions, orientations, or geometric changes and can learn broader patterns.

In deep learning, rotation, translation, scaling, shearing, flipping, cropping, and perspective distortion are a few geometric augmentation methods that are frequently employed. By using these geometric augmentation approaches, geometric changes may be added to the training data, making deep learning models more robust to differences in real-world images. This enables the model to work better even when objects appear in diverse orientations or postures in pattern recognition tasks like object identification, object classification, or picture segmentation.

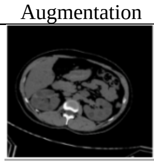
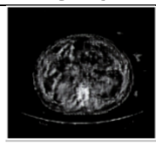
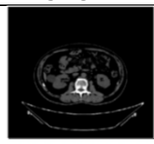
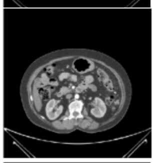
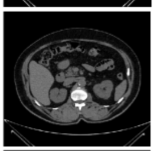
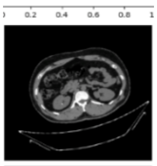
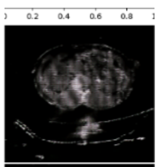
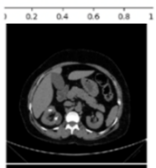
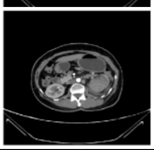
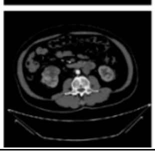
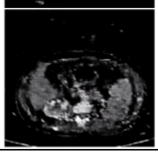
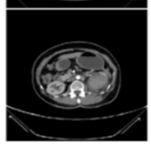
3. RESULTS AND DISCUSSION

Training, validation, and testing are performed on data augmentation before the prediction process. Geometric, GANs, SMOTE, and original data are used in the nazmul0087 dataset and primary data from hospitals. There are several classes of dataset types, with the amount of data from each training, testing, and validation shown in Table 1. CT scan image of kidney disease consists of cyst, normal, stone, and tumor after augmentation, original, GANs, and SMOTE are shown in Table 2.

Table 1. The number of train, test, and validation data in each class, the number of test data comes from primary data/hospital

Class	Train	Test	Validation	Dataset
Tumor	980	265	94	ORI
Stone	610	166	75	ORI
Normal	2356	657	271	ORI
Cyst	1612	457	178	ORI
Tumor	2367	265	250	AUG
Stone	2398	166	281	AUG
Normal	2316	657	260	AUG
Cyst	2376	457	260	AUG
Tumor	2362	265	264	GANs
Stone	2348	166	258	GANs
Normal	2399	657	268	GANs
Cyst	2348	457	261	GANs
Tumor	2345	265	286	SMOTE
Stone	2388	166	238	SMOTE
Normal	2377	657	252	SMOTE
Cyst	2347	457	275	SMOTE

Table 2. CT scan image results after original, augmentation, GANs, and SMOTE on kidney disease types

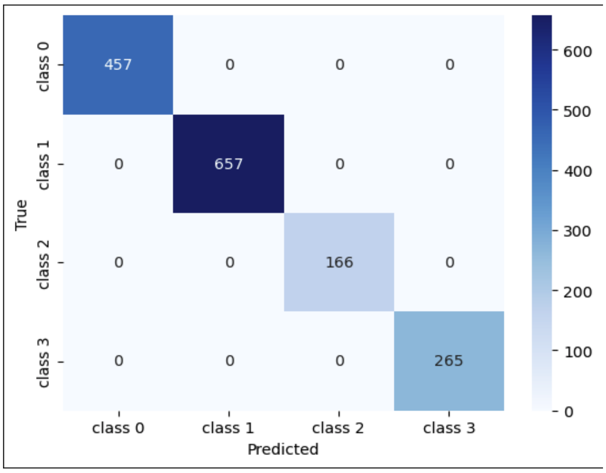
Class	Original	Augmentation	GANs	SMOTE
Cyst				
Normal				
Stone				
Tumor				

Training datasets of cyst, normal, stone, and tumor kidney disease images are used to train or build models. Then the validation dataset is used to optimize when training the model from images of cyst, normal, stone, and tumor kidney disease. The model is trained using a training dataset, then its performance during training is tested using a validation dataset, which aims to see whether the model's ability during training can recognize patterns in general. Validation datasets can also be used to see the accuracy of the model. After the model has been trained well and can recognize general patterns through high score accuracy, the next step is to recognize data testing. Testing data is used to test image models for cyst, normal, stone, and tumor kidney disease. The dataset sharing ratio used is 80% training; validation 10%; testing 10%. with the use of more sophisticated machine learning and deep learning will be applied to different data sets on medical images, so that the efficiency and effectiveness of CKD prediction can be improved at an early stage [31].

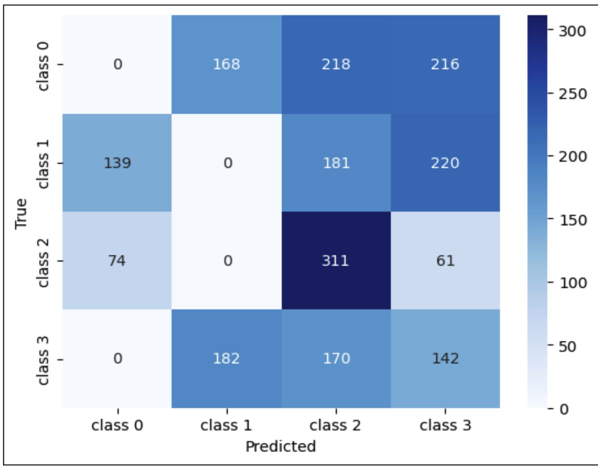
3.1. Performance confusion matrix original

3.1.1. Confusion matrix original

The results of Figure 6 show the confusion matrix of the original data of kidney disease cyst (0), normal (1), stone (2), and tumor (3) using public and primary/hospital datasets. Example data of the original confusion matrix from the training dataset (nazmul0087 dataset) of kidney disease cyst, stone, tumor, normal using the original data in Figure 6(a). Kidney disease images can be classified as cyst, normal, stone, and tumor accurately and without making any classification errors. The original confusion matrix of the kidney disease testing dataset using primary/hospital data is shown in Figure 6(b). The results of the confusion matrix from adding data to the kidney disease training data and testing data are shown in Figure 7.



(a)

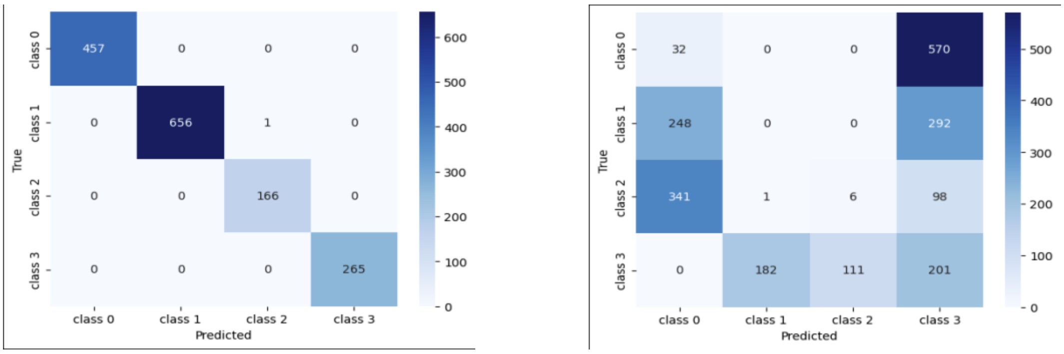


(b)

Figure 6. Confusion matrix results of original data on kidney disease (a) training data and (b) testing data

3.1.2. Confusion matrix augmentation

The results of Figure 7 show the confusion matrix results of augmentation data on kidney disease disease cyst (0), normal (1), stone (2), and tumor (3) using public and primary/hospital datasets. Example of confusion matrix augmentation from the training dataset (dataset nazmul0087) cyst, stone, tumor, and normal kidney disease using augmentation in Figure 7(a). Images of kidney disease cysts, normals, stones and tumors can be classified accurately and without misclassification. Augmentation of the confusion matrix on kidney disease testing data sets using primary or hospital data. The images of cysts, normal kidney disease, stones, and tumors in Figure 7(b) are classified as low accuracy values.



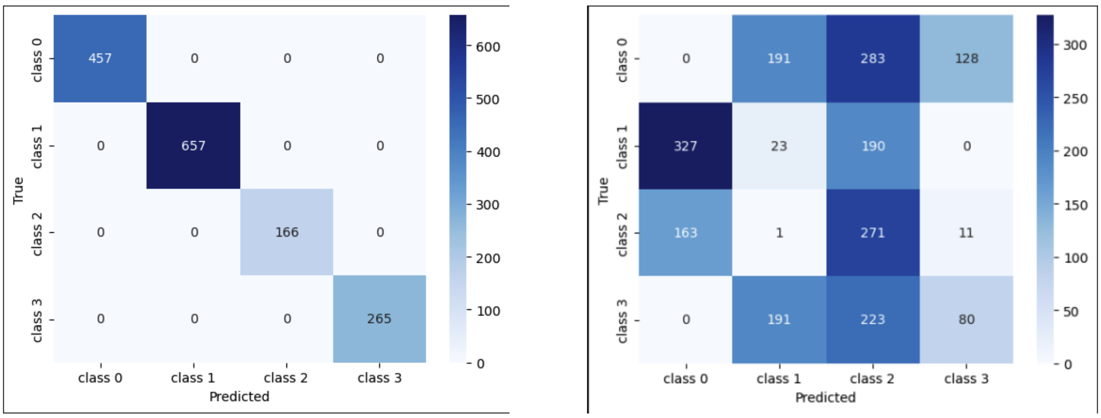
(a) (a)

Figure 7. Confusion matrix results of augmentation data on kidney disease (a) training data and (b) testing data

3.1.3. Confusion matrix generative adversarial networks

GANs are like a Rubik's cube. Once you know the trick to solving the cube, there are several ways to get the perfect cube. It can take up to 3.47 seconds (the current world record for a 3×3 Rubik's cube) and is easy to spot if you make a mistake. But if you don't know the trick to solving the cube, it will take a long time. The time and cost of GANs failure is quite high (considering training time and resource value), especially when you have limited resources and you may still be wondering what went wrong. Once you know the GANs dependency, it will be relatively easy to get the right solution.

The results of Figure 8 show the confusion matrix results of GANs data on kidney disease cyst, stone, tumor, normal using public and primary/hospital datasets. Sample confusion matrix GANs from the training dataset (dataset nazmul0087) kidney disease cyst, stone, tumor, normal by using GANs is shown in Figure 8(a). Pictures of renal illness There are no classification mistakes while classifying (0) cyst, (1) normal, (2) stone, and (3) tumor. The GANs confusion matrix of the kidney disease testing dataset using primary/hospital data is shown in Figure 8(b). The kidney disease images (0) cyst, (1) normal, (2) stone, and (3) tumor in Figure 9(a) are classified as having high accuracy value and Figure 9(b) as having low accuracy value.



(a) (a)

Figure 8. Confusion matrix results of GANs data on kidney disease (a) training data and (b) testing data

3.1.4. Confusion matrix SMOTE

The oversampling technique known as SMOTE is used to evenly distribute the number of samples in a dataset across the majority and minority classes. Samples from the minority class are chosen at random by SMOTE, which then combines them to produce new synthetic samples. This enhances the ability to classify views on imbalanced datasets. SMOTE, however, tends to add noise and degrade the effectiveness of classification prediction [32]. K-means SMOTE has been shown to improve classification performance on unbalanced data sets.

The results of Figure 9 show the confusion matrix results of SMOTE data on kidney disease cyst (0), normal (1), stone (2), and tumor (3) using public and primary/hospital datasets. SMOTE confusion matrix samples from the training dataset (dataset nazmul0087) of cyst, stone, tumor, and normal kidney disease using SMOTE in Figure 9(a). Images of kidney disease Cysts, normals, stones and tumors can be classified accurately and without misclassification. Figure 9(b) displays the SMOTE confusion matrix of the kidney disease testing dataset using primary or Hospital data. The accuracy results of the training model using augmentation, GAN, original, and SMOTE are shown in Figure 10.

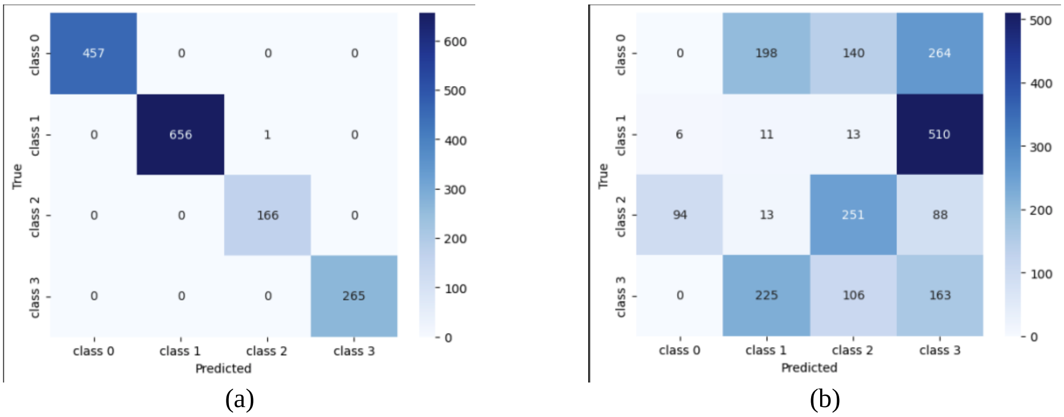


Figure 9. Confusion matrix results of SMOTE data on kidney disease (a) training data and (b) testing data

3.2. Accuracy graph of training model

The accuracy value of the training model (dataset nazmul0087) in terms of augmentation, GANs, original and SMOTE models, and kidney cysts, stones, tumors, and normal. The results of augmentation value are 99.93%, GANs 100%, original 100%, and SMOTE are 99.93%. In Figure 10, the results of the training model obtained a very high accuracy value, with perfect results. The accuracy results of training models using augmentation, GANs, original, and SMOTE.

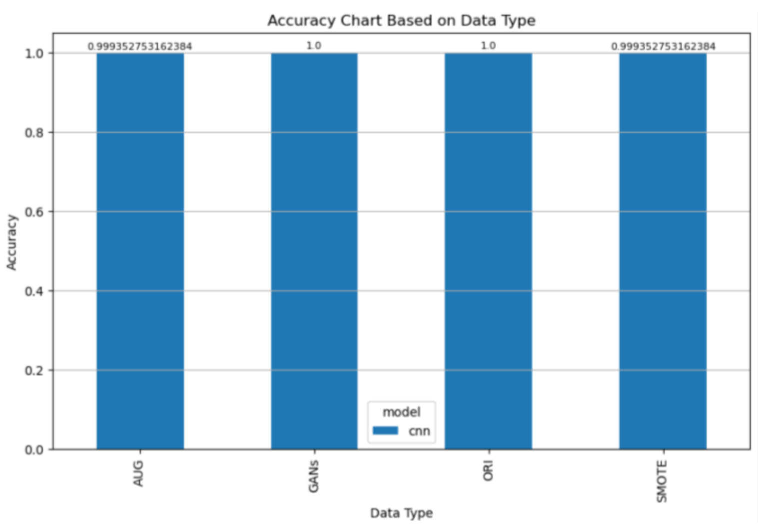


Figure 10. Accuracy results of the training model using augmentation, GANs, original, and SMOTE

3.3. Graph accuracy model testing

The results of the accuracy value of the testing model (primary dataset/hospital data) in the detection of kidney cysts, stones, tumors, and normal by using augmentation, GANs, and original and SMOTE models. The results obtained the value of augmentation 11.48%, GANs 17.96%, original 21.76%, and SMOTE 20.41%. In Figure 11, the results of the training model, the highest accuracy value is obtained in the original model. We recommend that the testing model be used with the original model so that it will get a high accuracy value in detecting kidney disease.

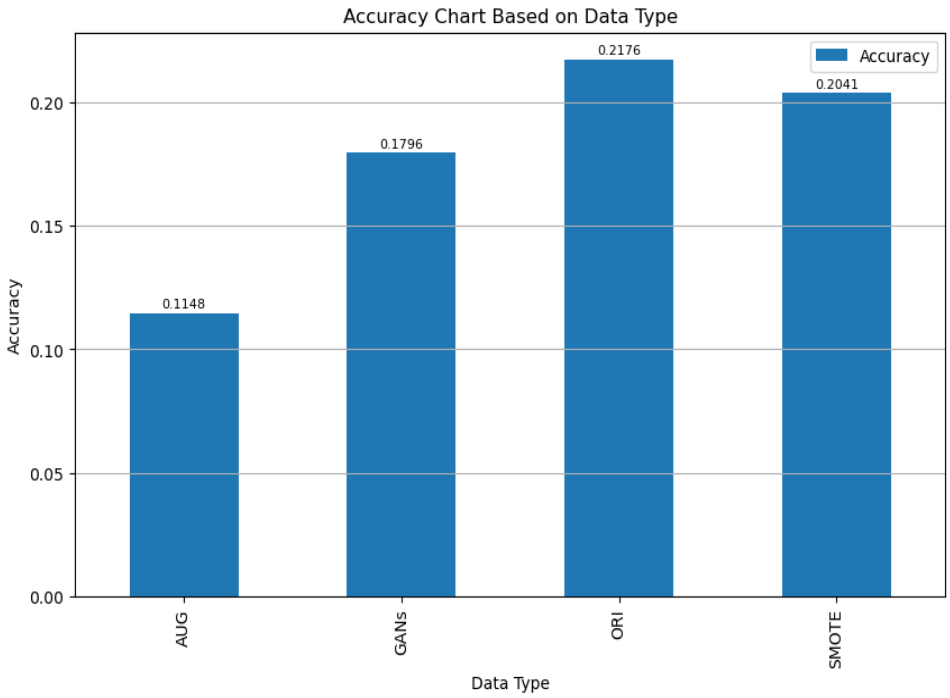


Figure 11. Accuracy results of testing models using augmentation, GANs, original, and SMOTE

The results of research on interpreting kidney disease detection that we found by conducting training data on the detection of cysts, stones, tumors, and normal kidneys obtained an augmentation value of 99.93%, GANs 100%, original 100%, and SMOTE of 99.93%. The results of the training model obtained very high accuracy values, with perfect results. the results of data testing in detecting kidney cysts, stones, tumors, and normal results obtained an augmentation value of 11.48%, GANs 17.96%, original 21.76%, and SMOTE 20.41%, so by using the original data the value obtained was higher so that it can help radiologists in detecting kidney disease. This is different from Supriyanto *et al.* [33] which stated that the interpretation of skin cancer images was correct using augmentation. The use of clinical data from various diseases will have an impact on the images used, such as to identify kidney stones, you can use CNN with the Alex Net DFCWTCNN algorithm to improve medical images, especially images of kidney stones [34]. The chronic kidney disease (CKD) early detection method uses binary wheal optimization algorithm (BWOA) feature selection [31]. Hybrid deep learning models can be used to improve kidney disease detection and classification by combining CNN models and CatBoost classifiers [35].

4. CONCLUSION

Providing deep learning insights for kidney disease detection using augmentation, GANs, original, and SMOTE techniques. Modeling with custom CNN for the data oversampling process does not have a significant influence on model evaluation performance, as well as when testing primary/hospital data, however using original data still provides the best performance in detecting kidney disease. This research still has shortcomings at the data processing stage, the research only carries out an oversampling process on the original data. So it is necessary to carry out future research such as the process of focusing objects or optimizing image quality first.

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