

Mobile Based Android Application for Identification and Reduction of Intussusception

¹Sandeep S., ²Suma M. S.

Submitted: 15/09/2023

Revised: 29/10/2023

Accepted: 13/11/2023

Abstract: Intussusception is abnormality in intestine when a invasion of one portion of intestine invades into adjoining part of another. Diagnosing and classification intussusception from images of ultrasonography and computed tomography can be challenging task for radiologist and pediatrician. Reduction of the intussusception is achieved by surgical and non-surgical methodologies. The non-surgical reduction methodologies are air enema and liquid enema techniques. The objective of this study is to identify and reduce intussusception by classifying intestinal CT scans and ultrasonography images to differentiate between healthy and diseased subjects. To concentrate on the challenge of identification and reduction of intussusception, an android application titled “Successful Detection and Reduction of Intussusception” (SDRI), has been designed and developed. To improve the efficacy of treatment and increase patient survival, an accurate diagnosis of an intestinal intussusception is crucial. Nevertheless, it is challenging to manually assess many Computed Tomography (CT) and Ultrasonography pictures captured in a hospital. As a result, more accurate computer-based intussusception identification techniques are needed. Numerous initiatives have looked at traditional Machine Learning (ML) techniques to automate this procedure in recent years. Recently, interests in utilizing deep learning approaches to achieve better reliably and effectively diagnose intussusception has increased. This leads to the development in this research of an improved Convolutional Neural Network (CNN) for precise categorization of intestinal CT images and Ultrasound images. Hyper-parameters are optimized for CNN layer training via the Resnet Reduction of the intussusception by non-surgical methodologies can be achieved by the same android app SDRI via Bluetooth way of communication. To treat infantile intussusception, novel equipments have been developed, the air enema technique and liquid enema technique has been used. Through these techniques, intussusception can be reduced, and the rate of reduction is faster compared to other existing methods. The equipments incorporate a microcontroller which is programmed in Embedded C to achieve operation. The deliverable equipment executes a function that regulates outflow of the air and liquid. These equipments offer a secure and forth right technique of treating intussusception. The proposed solution is a reliable, unsophisticated, and reasonably priced piece of equipment that may be employed in Out-Patient Departments, Clinics, and Hospitals. The developed systems can be implemented practically after the successful clinical trials. . The suggested model is evaluated and deployed to SDRI application using the cancer imaging archive dataset. With 89% accuracy, 93.0% sensitivity, and 75% specificity, the improved CNN model achieves the acceptable range of accuracy.

Keywords: Intussusception, Android, Machine Learning, Pneumatic Reduction, Enema, Microcontroller, Computed Tomography.

Abbreviations: CNN: Convolution Neural Network, SDRI: Successful Detection and Reduction of Intussusception, UI: User Interface, DNN: Deep Neural Network, ANN: Artificial Neural Network, YOLO: You only look once algorithm, AUC: Area under the ROC curve, ROC: Receiver operating characteristic curve.

1. Introduction

Intussusception is idiopathic cause in the intestine where the telescopic structures will be formed in the intestine. One portion of intestine will invaginates into another. This is a life risk as the blood flow in the intestine will stop due to telescopic structure. The biological cause of the intussusception is by microorganism majority of risk were found by viruses, bacteria and fungus. The major symptoms involve swelling, vomiting and passing the blood stools. This intussusception problem is majority

found in children up to age of five to six years. Most of the cases comparatively issue is found in male kids compared to female ones. In some children, it is caused by a condition that the child is born with, such as a polyp or diverticulum [1].

Intussusception is diagnosed by ultrasound scanning technology or chromatography scanning methods [2]. As early as intussusception is identified, the solution is reducing intestine to normal state, using non surgical methods is preferable as it avoids usage of anesthesia and operating internally. An air contrast enema or liquid contrast enema can be used to reduce intussusception. In pneumatic reduction or hydrostatic methodology the air or water will be transferred to anus by maintaining the pressure inflow inside the human body. In the present technology manually hand gauge is used to control the

¹Department of Electronics and Communication Engineering, B.M.S. College of Engineering, Bangalore, Karnataka, India
<https://orcid.org/0000-0001-5155-9507>, sandeeps@bmsce.ac.in

²Department of Medical Electronics, B.M.S. College of Engineering, Bangalore, Karnataka, India
<https://orcid.org/0000-0002-7995-5568>, sumams.ml@bmsce.ac.in

air outflow. These non operational methods will reduce the intussusception as per the requirement [3, 4]. In liquid enema a liquid mixture of saline, barium or Olive oil mixed saline is used instead to fix the blockage by passing the liquid inside the intestine by monitoring the same with radiologic devices [5, 6]. The repeated enemas can be done still the intussusception is reduced.

Overall, intussusception can be easily and successfully reduced by air enema and liquid enema techniques. According to the literature survey sources, many researchers have worked on solving this problem. Where in a device designed by Stein-Wexler et al. [7] replicates fluoroscopic intussusception reduction using air. The contraption consists of a doll with a cylinder that resembles the human colon in terms of tension and strain. A regular hand-held air reduction pump can be used to pump air into the cylinder via a rectal catheter. A sensor detects the pressure within the chamber and sends signals to a computer, which displays visuals of actual intussusception reductions dependent on the pressure maintained within the device. J Thomas et al. [8] invented a device for insufflations of air reliably at safe pressures for the effective removal of intussusception in youngsters under fluoroscopic supervision. The device's outcomes were comparable to those of saline enema minimization under ultrasound supervision. To suit the requirements of an air enema, the air in sufflation device was developed. Berdon et al. [9] developed a novel device for pneumatically reducing infantile intussusception. The gadget is made up of a reusable hand-held high-pressure hose and insufflators that are linked to a biodegradable enema tip and tubing system. The device may be operated with one hand thanks to its assembly, which maximizes user control over the air reduction process. The technique has been utilized to treat individuals who are immune suppressed.

Y. Mensah et al. [10] explained the hydrostatic reduction using ultrasound scanner technology. The analysis says 75% of the patients got cured the other 25% of the patients intussusception was not reduced successfully. Ademola Olusegun Talabi et al. [11] With help of Sonography technique hydrostatic saline enema reduction has been utilized. The success rate of hydrostatic reduction with saline enema was 84.4%. Their study found Ultrasound guided hydrostatic reduction is one the better approach to reduce intussusception.

Diagnosis can be carried with the aid of medical imaging. Typically ultrasound is preferred for children and CT for adults. The classical appearance of intussusception in the image can be identified in the doughnut shape in the transverse view and can be seen as

sandwich in the longitudinal view. Intussusceptions can be classified into four types based on location: a) ileo-cecal, b) ileo-colic, c) Colo-colic, d) entero-enteric [12].

Deep convolutional neural networks (CNNs) are widely employed in the domains of radiology and medical image analysis for image recognition and categorization. In clinical settings, such as primary care institutions, where there is little to no knowledge of intussusceptions [13]. During emergency situations, an automated method for screening plain abdominal radiographs and prioritizing positive images for rapid review and diagnosis is necessary. This may reduce any delays in diagnosing intussusception and reduce the incidence of misdiagnoses [14].

Deep CNN models need large, carefully selected training datasets with considerable visual heterogeneity, external validation testing, and optimization of hardware and settings to provide excellent accuracy and performance in varied clinical scenarios [15, 16]. Based on multimodal breast-ultrasound pictures, [17] the authors created an explainable deep-learning system that predicted BI-RADS scores for breast cancer as accurately as seasoned radiologists [18]. A deep-learning AI model (ThyNet) to distinguish between cancerous tumor and benign thyroid nodules with the goal of determining how ThyNet may aid radiologists in performing diagnostic procedures more effectively and avoiding needless small needle aspiration. In order to detect and diagnose focal liver lesions from ultrasound pictures, [19] authors constructed a deep learning network. The AI model identified and identified common focal liver lesions. Although the use of artificial intelligence in still in pediatrics is its infancy, it is widely employed in the identification and categorization of abnormalities in breast, thyroid, liver, and other ultrasound pictures.

2. Materials and Methods

2.1 SDRI Application Overview

SDRI android application for detection and reduction intussusception has been developed. Deep learning model has been deployed on SDRI application. The model is trained by comparing normal and positive intussusception images. Once the radiologist scans a patient, can upload the scanned images of the same into the cloud. The Deep learning algorithm model designed to predict case of intussusception is also deployed in the same cloud instance. The cloud based technology used is FIREBASE. If the positive case is diagnosed therapeutic system can be operated successfully via Bluetooth mode of communication. The complete flow of the system is represented in the Figure 1.

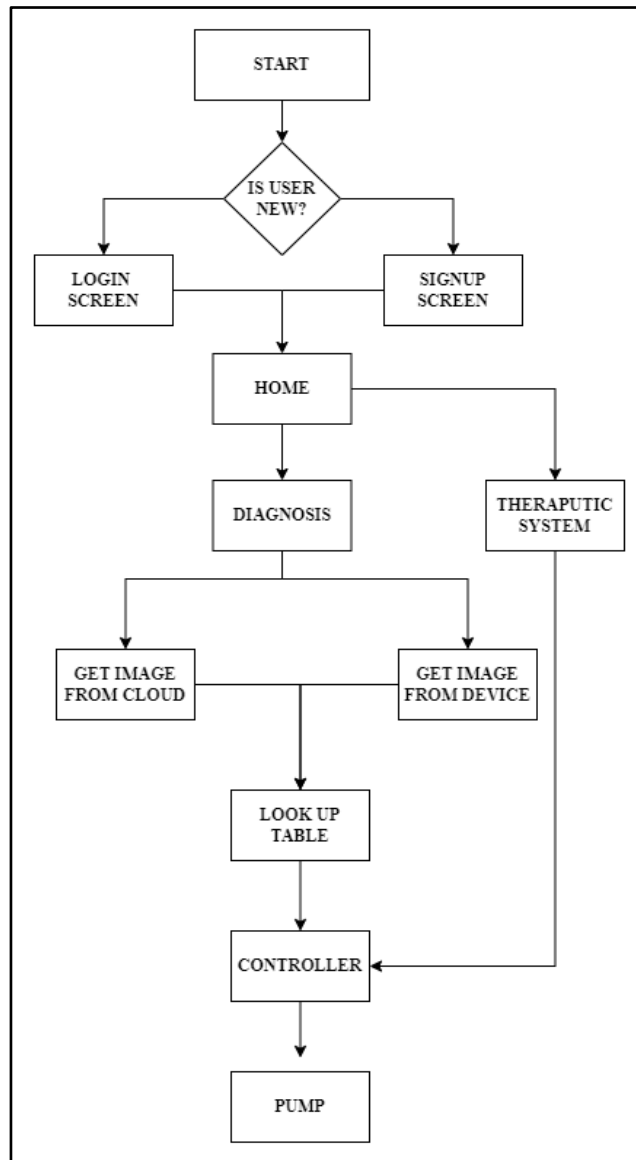


Fig 1: Complete architecture of the proposed system

2.2 User Instruction for End User

Once the doctor log into the application, Menu opens up and various options are available. If the user selects the option Doctor, it displays all the pediatricians and

radiologists who have registered into this app. Internally any health care provider registered into this app will also have access to contact the peer staff. The home page will display Diagnosis and Threupatic system. The pictorial view of Home screen is represented in the Figure 2.

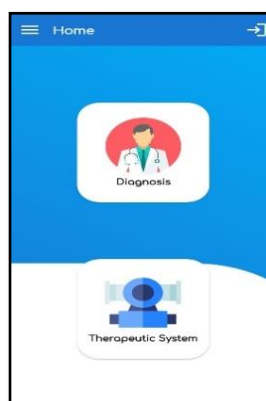


Fig 2: Home screen View from android application

The complete android application class diagram is shown in the Figure 3. The figure explains the interconnection

between the different classes. It also shows the member variable of each class along with its access specifier.

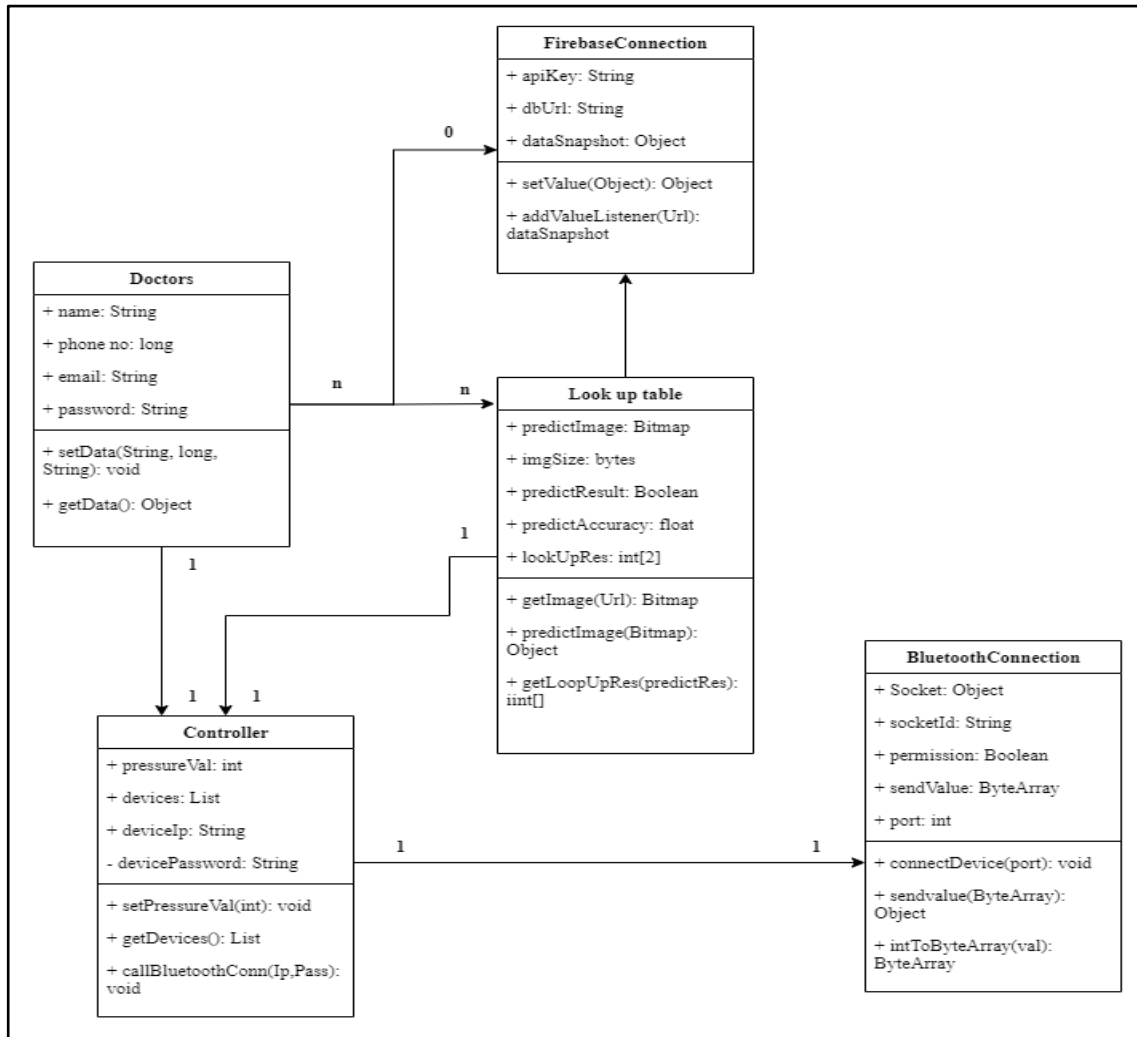


Fig 3: Class Diagram of Android Application

2.3 Diagnosis

Datasets

Totally 500 normal/intussusception of Ultrasonography and CT modality was used for the experiment. 480 images were used for training and the remaining 20 were used for testing. The 450 images were further randomly split into training and validation. The images were of the size 2452x2192. The images were pre-processed before training. A simple Gaussian smoothing filter of (n x n) size kernel was used to remove noise in the images. The images were scaled and cropped manually to size 1226x1092 to have better context of intussusception. The intussusception was manually detected and cropped based on visual detection.

Training

A 32 layer Resnet model was used for training. A Resnet is a CNN based deep model with residual blocks and skip connections. This alleviates the gradient vanishing problem that is prevalent in deep neural networks with multiple layers. The network contains Batch Normalization layers that help improve generalization. Max Pooling layer is used to subsample the images before passing the image to the Residual Blocks. Rectified Linear Units [ReLU] activation is used to add non-linearity between the layers. The final activation layer is a simple sigmoid activation which classifies an image as intussusception positive or negative. Flowchart for proposed method is depicted in Figure 4.

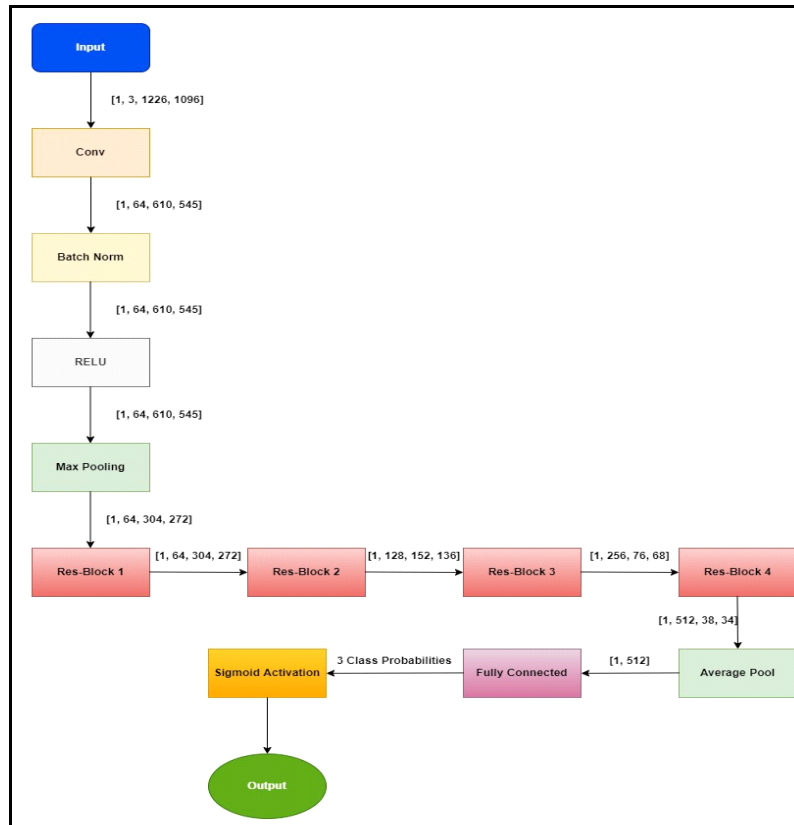


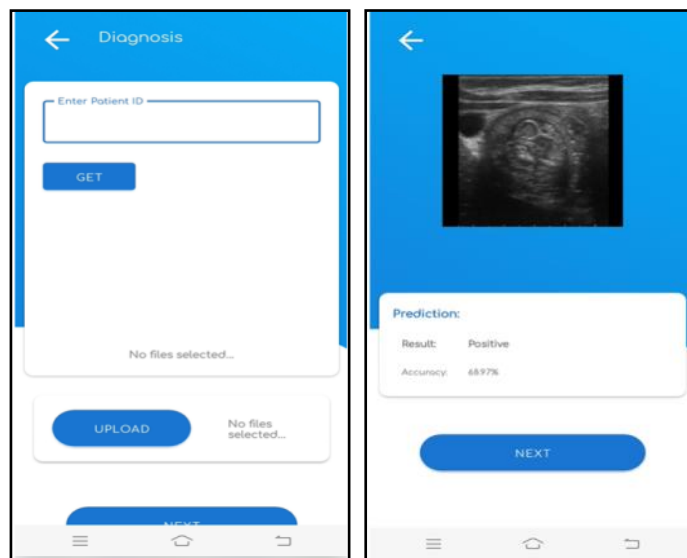
Fig 4: Flowchart for the proposed technique

The model was built using PyTorch and trained from scratch without pre-trained weights. The weights were randomly initialized for each round of training. The model was trained with Binary Cross Entropy Loss. Adam Optimizer with a learning rate of 0.0001 was used for training. A batch size of 15 with validation split size of 0.25 was used for training. Early stopping patience of 3 was used to prevent over fitting. The model was trained for 50 epochs. Early stopping patience kicked in at the 40th epoch indicating no significant change in performance since the 37th epoch.

The early stopping patience was implemented to account for changes in validation loss and F1 score and is

independent of training loss. The training loss was used purely as an observational metric. The model state after each epoch was saved as a checkpoint file with an option to save the model as a 'onnx' file. The model state can be restored to any epoch using the checkpoints.

The Figure 5a and Figure 5b represents the Android user interface design of diagnosis. The images will be retrieved from the cloud and will be displayed on mobile screen along with the diagnosis report. The report explains positive or negative intussusception. The app provides alternative method if the hard copy of report is available, the image of same can be taken and uploaded.



(a)

(b)

Fig 5(a): Android UID of Diagnosis Patient ID with Upload option

Fig 5(b): Android UID of Diagnosis Patient image displayed with Prediction

2.3 Therapeutic System

If a patient is tested positive for intussusception, the next process will be stepping into the therapeutic system. In this phase doctors can imply air enema or liquid enema to treat intussusception. To perform the enema treatment

two different devices are assembled. Any of the devices depending on the choice of enema being performed must be connected through Bluetooth to the mobile from the android application. The android user interface of therapeutic system is shown in Figure 6 below.

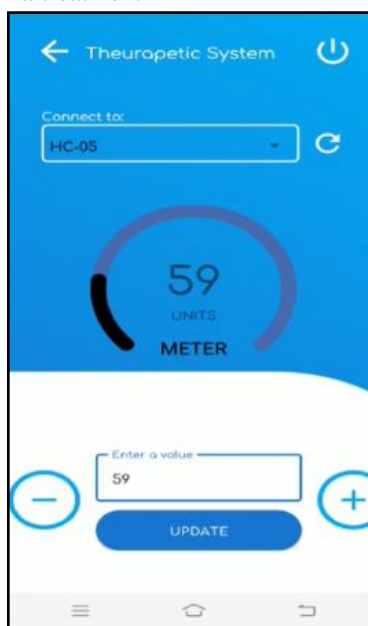


Fig 6: Android user interface design of air and liquid enema device.

Bluetooth Controlled Therapeutic System

Electronic operator air enema and liquid enema passing device are once assembled. Microcontroller is used for control operation. The pressure outlet of air and liquid are measured. The whole device is controlled by input provided through the android application. The air or

liquid outflow is measured and monitored. Through suction tube, air or liquid can be transferred to anus of the patient. Repeated enema can be performed if required. The below Figure 7 shows the air enema and liquid enema devices which is controlled by Bluetooth Android based Mobile device.

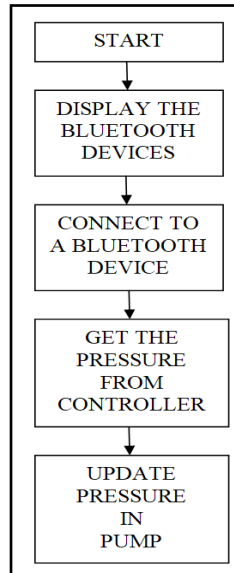


Fig 7: Flow Diagram of Therapeutic System

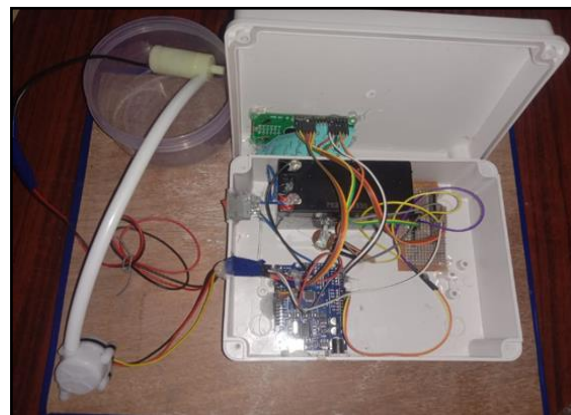
3. Results

Once Patient ID is entered in the android based SDRI application, the data (images) is fetched through the cloud and the result is displayed. The results obtained might be positive or negative based on the presence of intussusception, which will be displayed along with the accuracy. If it is the positive case, it will be redirected to

therapeutic system. The radiologist and pediatrician can further decide to operate air enema or liquid enema. Based on that decision either one of the device can be operated. The value entered in android app is transferred from mobile to Bluetooth controlled device in form of packets, the same will be converted and updated in the microcontroller which will run the operating device. The same prototype is represented in Figure 8a and Figure 8b.



(a) Air Enema Prototype Device



(b) Liquid Enema Prototype Devices

Fig 8: Prototype Devices

Area under the ROC Curve (AUC) and Receiver operating characteristic curve (ROC) were used as performance metrics. Loss curves were used to validate training performance. A Confusion Matrix is also presented with Sensitivity and Specificity in detecting

intussusception. The performance metrics are represented in Table 1. The intussusception case for 1 dataset is shown in the following Figure 9. ROI highlighted depicts the unhealthy case seen in the image.

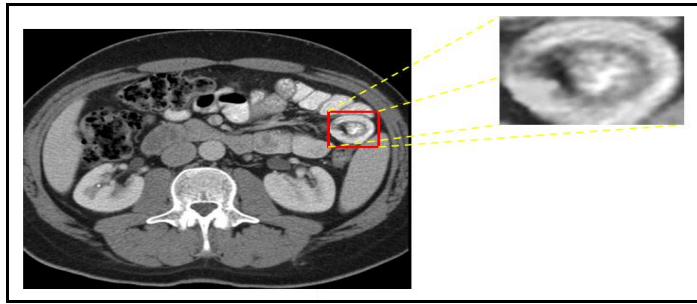


Fig 9: Intussusception case in the selected region of interest

Table 1: Performance metrics such as AUC, accuracy, sensitivity and specificity tabulated.

Metric	Value
AUC	0.8416
Accuracy	0.8947
Sensitivity (normal)	0.93
Specificity (intussusception)	0.75

The AUC is presented in Figure 10. The graphic shows that AUC drops since the model is presently biased towards intussusception. As a result, the performance of

the prediction of intussusception data suffers. The positive class here is considered to be normal and the negative class is intussusception.

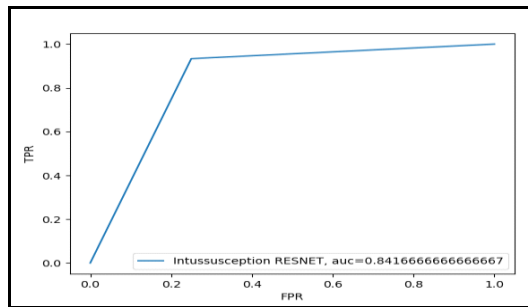


Fig 10: ROC with AUC of 0.8416

The confusion matrix for a test set of 19 images is depicted in Figure 11. The network was tuned to classify normal images with higher sensitivity. This can be observed with better True results correctly classifying

normal images. As seen in Table 1, the proposed technique is able to reach a sensitivity of 93% in comparison to normal images, whereas model manages a specificity of 75%.

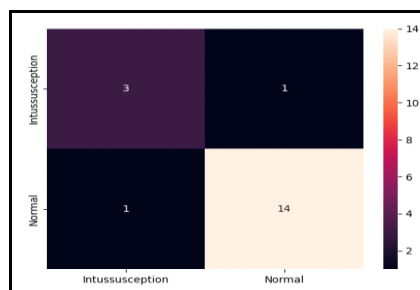


Fig 11: Confusion Matrix

4. Discussion

The SDRI application is used to diagnose and recover intussusception. The deep learning model trained to

classify intussusception images performs successfully with an accuracy of 89%. The model is currently tuned to be more sensitive in detecting normal cases. The classifier is biased to the intussusception class. This can

be mitigated by increasing the training samples and also incorporating diverse cases of normal and intussusception images. Due to a lack of intussusception data, (Table 1) performance measures have a specificity that is lower than sensitivity. The detection stage is currently a manual review process. The images are cropped based on visual detection and confirmation of intussusception or in case of normal images. This process can, however, be automated using Deep Learning. This would provide a bounding box around suspected intussusception. A false positive reduction network could be then used to increase the specificity of the algorithm. With the help of android application the electronic devices can be operated to reduce intussusception. The pressure outflow can be monitored in the device.

5. Conclusion

The developed android application SDRI along with the deployed Deep learning model for detection and Blue tooth controlled control system is an end to end model which can be utilized for detection and recovery of intussusception. To suit the requirements of an air enema and liquid enema techniques, Bluetooth based control system will be operated. The SDRI application has special qualities including the ability to diagnosis and reducing pediatric intussusception. The system will demonstrate its value. The SDRI application is functional, and pediatricians can utilize it efficiently after the clinical trials. The application and devices is very cost effective, portable user friendly and can be used in Clinics also. The application avoids the surgery and reoccurrence by using enema techniques. Both air and liquid enema is achieved with the help of SDRI.

References

- [1] Reichert MC, Lammert F. The genetic epidemiology of diverticulosis and diverticular disease: Emerging evidence. *United European Gastroenterol J.* 2015 Oct;3(5):409-18. doi: 10.1177/2050640615576676. PMID: 26535118; PMCID: PMC4625748.
- [2] Dadlani A, Lal S, Shahani B, Ali M. Ultrasonography for the Diagnosis of Intussusception in Children: An Experience From Pakistan. *Cureus.* 2020 Aug 11;12(8):e9656. doi: 10.7759/cureus.9656. PMID: 32923254; PMCID: PMC7482991.
- [3] Dung ED, Shitta AH, Alayande BT, Patrick TM, Kagoro B, Odunze N, Rikin C, Chirdan LB. Pneumatic Reduction Of Intussusception In Children: Experience And Analysis Of Outcome At Juth, Jos, A Tertiary Health Centre In North Central Nigeria. *J West Afr Coll Surg.* 2018 Oct-Dec;8(4):45-66. PMID: 33553051; PMCID: PMC7861193.
- [4] Chukwubuike KE, Nduagubam OC. Hydrostatic reduction of intussusception in children: a single centre experience. *Pan Afr Med J.* 2020 Aug 11;36:263. doi: 10.11604/pamj.2020.36.263.21380. PMID: 33088392; PMCID: PMC7546016.
- [5] DENENHOLZ EJ, FEHER GS. Barium reduction of intussusception in infancy. *Calif Med.* 1955 Jan;82(1):8-12. PMID: 13230908; PMCID: PMC1532242.
- [6] Beger B, Duz E, Kizilyildiz BS, Akdeniz H, Melek M, Agengin K, Avci V, Sonmez B. A new enema for treatment of intussusception with hydrostatic reduction: Olive oil. *Afr J Paediatr Surg.* 2019 Jan-Mar;16(1):14-16. doi: 10.4103/ajps.AJPS_83_17. PMID: 32952134; PMCID: PMC7759078.
- [7] Stein-Wexler R, Sanchez T, Roper GE, Wexler AS, Arieli RP, Ho C, Li JC, Ozpinar A, Soosman SK. An interactive teaching device simulating intussusception reduction. *Pediatr Radiol.* 2010 Nov;40(11):1810-5. doi: 10.1007/s00247-010-1764-x. Epub 2010 Jul 21. PMID: 20652235; PMCID: PMC2950270.
- [8] Thomas RJ, Rakesh S. An air insufflation device for reduction of intussusception in children. *J Indian Assoc Pediatr Surg [serial online]* 2008 [cited 2022 Nov 17];13:94-6.
- [9] Berdon, W.E. On the following review entitled "Pneumatic reduction of ileocolic intussusception in children". *Pediatr Radiol* 18, 2, <https://doi.org/10.1007/BF02395748>
- [10] Mensah Y, Glover-Addy H, Etwire V, Appeadu-Mensah W, Twum M. Ultrasound guided hydrostatic reduction of intussusception in children at Korle Bu Teaching Hospital: an initial experience. *Ghana Med J.* 2011 Sep;45(3):128-31. PMID: 22282581; PMCID: PMC3266142.
- [11] Talabi, A.O., Famurewa, O.C., Bamigbola, K.T. *et al.* Sonographic guided hydrostatic saline enema reduction of childhood intussusception: a prospective study. *BMC Emerg Med* 18, 46 (2018). <https://doi.org/10.1186/s12873-018-0196-z>.
- [12] Smith, D. S., W. A. Bonadio, and J. D. Losek. "Abdominal x-rays in the diagnosis and management of intussusception." *Pediatr Emerg Care* 8 (1992): 325-327
- [13] Gulshan, V. *et al.* Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA* **316**, 2402–2410 (2016).
- [14] Esteva, A. *et al.* Dermatologist-level classification of skin cancer with deep neural networks. *Nature* **542**, 115–118 (2017).

- [15] Parashar, U. D. *et al.* Trends in intussusception-associated hospitalizations and deaths among US infants. *Pediatrics***106**, 1413–1421 (2000).
- [16] Buettcher, M., Baer, G., Bonhoeffer, J., Schaad, U. B. & Heininger, U. Three-year surveillance of intussusception in children in Switzerland. *Pediatrics***120**, 473–480 (2007).
- [17] X. Qian, J. Pei, H. Zheng *et al.*, “Prospective assessment of breast cancer risk from multimodal multiview ultrasound images via clinically applicable deep learning,” *Biomedical Engineering*, vol. 5, no. 6, pp. 522–532, 2021.
- [18] S. Peng, Y. Liu, W. Lv *et al.*, “Deep learning-based artificial intelligence model to assist thyroid nodule diagnosis and management: a multicentre diagnostic study,” *The Lancet Digital Health.*, vol. 3, no. 4, pp. e250–e259, 2021.
- [19] T. Tiyyarattanachai, T. Apiparakoon, S. Marukatat *et al.*, “Development and validation of artificial intelligence to detect and diagnose liver lesions from ultrasound images,” *PLoS One*, vol. 16, no. 6, p. e0252882, 2021.
- [20] Wiling, B. (2021). Locust Genetic Image Processing Classification Model-Based Brain Tumor Classification in MRI Images for Early Diagnosis. *Machine Learning Applications in Engineering Education and Management*, 1(1), 19–23. Retrieved from <http://yashikajournals.com/index.php/mlaeem/article/view/6>
- [21] Maruthamuthu, R., Dhabliya, D., Priyadarshini, G.K., Abbas, A.H.R., Barno, A., Kumar, V. V. *Advancements in Compiler Design and Optimization Techniques (2023)* E3S Web of Conferences, 399, art. no. 04047