Tony [00:00:04] Welcome to Code Together, a podcast for developers by developers where we discuss technology and trends in industry.

Tony [00:00:11] I'm your host, Tony Mongkolsmai.

Tony [00:00:17] L&T Technology Services, LTTS, is a pure play engineering services provider. Today, we're going to talk about their chest X-ray, radiology suite, Chest-rAi., which uses deep learning to improve turnaround times for patients to receive their chest X-ray results. We are joined today by Dr. Nandish S, who has more than 12 years of experience working in the health care domain. He received his PhD from Manipal Academy of Higher Education with a focus on medical image processing, visualization and analysis. He is a senior member of IEEE and previously held the position of vice chair of the IEEE-EMBS Bangalore Chapter. Welcome to the podcast, Dr. Nandish.

Nandish [00:00:54] Yeah, thank you Tony. Thank you for the introduction.

Tony [00:00:57] Yeah, absolutely. And can you tell us a little bit about why Chest-rAi matters right now? Why is it important for us to have this solution in a timely manner?

Nandish [00:01:07] Yes. Before talking about the Chest-rAi solution, I would like to bring in the the pain points or background, whether radiologists or the patients. So when we consider that recently, every one of us have experienced the pandemic due to COVID 19 or earlier to COVID or post-COVID will see the very huge volume of chest X-ray images which are populated at the diagnostic centers or health providers. So when there is a huge volume of chest X-ray images, the radiologist, the time spent by the radiologist and the time spent by the patient, both we need to consider.

Nandish [00:01:44] So considering the pain point that the radiologist will look into the images from the viewing of the images until the reporting and the number of volumes. So that takes the more time for reporting for one patient and the patient wait time also. We built this solution to assist the radiologist, not to replace the radiologist. And here we are not going to identify, detect or classify any just diseases, but it helps the radiologist in finding the symptoms or identifying the findings on the images.

Nandish [00:02:17] So we have considered 18 different diseases of lung, which is identified through the chest X-ray images and all those chest diseases what we have identified 18 diseases. Out of 18 diseases, we have common 32 findings of that. So these are the 32 findings and we have used ten of it, ten findings in our solutions. And the eleventh one is the no findings, if we consider these findings right, it can be a effusions or some lesions which is present in the chest area or also the supporting devices, devices like pacemakers and which is present. So there are such ten different findings and plus normal. When we speak about a normal image also...identifying it as a normal also is a such an important thing because if the radiologist look into the images, if he can see the abnormalities, it will be quicker so he can visually identify what is the abnormalities there and he will report it. When there are the normal cases, that is the challenge where the radiologists don't even want to miss a minute abnormalities from the images. Where he spends more time and telling that yes, this case is normal. Telling this, identifying the image as in normal itself reduces a lot of time for radiologists and hence directly it influences the waiting time for the patient. So in that way, we can also prioritize those cases from the servers. Where radiologists need to give more time and looking into what images.

Tony [00:04:03] So in this case, when you're talking about assisting the radiologists, there has been a lot of solutions that we've seen coming out, you know, in radiology, where people are using AI to look at images and try to identify different types of diseases. In this case, it sounds to me like you're trying to identify which X-ray films a doctor should look at to help them kind of categorize what's potentially an issue and what potentially is normal. Is that correct?

Nandish [00:04:35] Yes, potentially not the disease we are identifying. As I said, there are 18 diseases out there and 18 diseases have a common symptoms are common findings in the images. So we are identifying those findings. So that will help the doctor to talk about what disease that person can be having it. So it will assist the doctor in finding those abnormalities.

Tony [00:05:02] Okay. How often do you guys update this model and how do you make sure that that happens and is rolled out to customers in the right way?

Nandish [00:05:11] Yeah Tony, as I said, for the 18 diseases we have 32 findings, right? So we have considered only ten findings as of now. So we can and answered concerning the remaining other findings, but also to build a AI model, right when we speak, we need to have a balanced dataset. So to consider the other findings, we need to have enough number of image data. So we are working on that, enhancing it or adding more findings to this solution is what we are having.

Tony [00:05:44] How do you guys make sure that one that your model is trained appropriately? How do you make sure that the inputs are correct? And then how do you make sure that patient security is covered? So when you're actually doing these things and building your pipelines, that we have the right level of security so patients can be confident that their images are secure.

Nandish [00:06:06] Yeah. First coming into the patient security, right. We have adopted the anonymization tool, right? It de-identifies the patient information before giving it to our model where we provide it to our users when they first run the images through our anonymization tool and then it will be fed into the AI solutions what we have. And coming into the how do we access it and the model more often we take help, leverage the radiologist or the trained radiologists who are associated with us and assessing the outcome of the AI predictions.

Nandish [00:06:49] So the first step where we assess is basically technically on a few of the metrics like precision and recall, that is the first step we look into. And the next step is we leverage the users, such as the trained radiologist who are associated with us. We take our take we take their feedback on the predictions. And also, if there are any discrepancies, then after a few such cases, our model have a capability of retraining it.

Tony [00:07:23] Okay. And we, because again, because we're looking at health care, obviously accuracy is important. We want to make sure that the patients get the right answers as quickly as possible, which is what Chest-rAi is enabling. Can you talk a little bit about how accurate your methodology is and how you guys determine which images fall into which categories?

Nandish [00:07:47] Okay. When we speak about the accuracy, our solution, what we have 95% accuracy which has been tested and validated with. And when we speak about which category the how do we guarantee the accuracy? For as I said, it is more of the help of our users who are the trained radiologists to give us a feedback on the prediction given up. And there and also before reporting, we need to have a human intervention that doctor before reporting the doctor the cross-check it and whether the predictions are made is right or wrong or if it is right or wrong in terms of is it a true positive or negative false positive or false negative based on the feedback from the doctors. So we will make it more accurate.

Tony [00:08:39] When you go to a doctor that's using your solution. You know, if I'm a patient, I guess my thought would be I want to make sure that a doctor is looking at my image rather than letting AI make that decision. So is it true that a doctor is always going to look at my image and you guys are just trying to help them classify it? Or is it the case that sometimes the AI says, oh, this is normal? You know, there's no need for the doctor to examine this X-ray film?

Nandish [00:09:06] No, not at all. The doctor will look into the images. Our solution will help the doctor. And in assisting him, him on her cases, whatever the doctor is looking at the images, he will be looking at the patient's images. So our AI solution will help the doctor. It doesn't, never replaces him.

Tony [00:09:25] Okay, good. I think that'll make all of our listeners feel a little more comfortable about the technology. And also, I notice that you guys are using the image technology kind of image recognition, right, to help assist. But I think you guys also use some type of natural language processing as well. Is that true?

Nandish [00:09:45] Natural language processing. It is mainly for the reporting for grammatically and clinically accurate reporting as required. So for that, we also use some pre-trained transformers along with the clustering and scoring models. Scoring models, what we use here is radiology finding quality index for the purpose of recording.

Tony [00:10:07] So the radiological finding quality index. Can you talk a little bit about that? Is that something that you guys came up with yourself or is that something that you've used from like third parties? Is it something standard or is it something custom?

Nandish [00:10:19] Like is that something standard where we have this RF quality index, those are the scoring models along with the testing and we have used the Pre-Trained transformers for that. That is mainly for grammatically and clinically accurate report generation.

Tony [00:10:36] So we talked a little bit in our meeting before we actually started recording the podcast about that. Potentially, this enables multiple workflows for both hospitals and individual radiologists. Can you talk a little bit about what the expected use case is and how you guys are planning to help radiology departments around the world?

Nandish [00:10:53] Yes. And when we talk about our users, right, mainly the other radiologists, when we look into the radiologists, the radiologists, few radiologists will be visiting multiple centers or it will be in the one healthcare provider. When we talk about the provider, it can be a hospital.

Nandish [00:11:08] So we have two different workflows where it can be used at the hospital and one at the radiology for the individual radiologists. When we speak about the hospital based workflow. So our solution is capable of integrated with the Dicom PACS system. The PACS is the picture archiving and communication system, it stores all the medical items which are supported by Dicom. So our solution is capable of fetching the studies from the PACs and then it will be created the dashboard out of the PACS images and where the doctors can see all the cases in the dashboard and he can click on one case and we have the option of Ask AI.

Nandish [00:11:51] It will be our normal image will that every hospital will be having along with their imaging modalities. So this will be one of them similar to that, it will be in the normal software which is given it is provided with other imaging modalities also. So this will just fit in with the radiology department connected to their PACs where doctors can see all the images here. They can fetch it from the PACs. And while we viewing the images, we have the option of Ask AI. So once they click on that Ask AI, so the prediction will come on the screen. And it is not only the prediction, it also identifies, localizes the region and give the annotations as per the size of the abnormality or as per the findings. So along with the predictions, they get the localization and also they get the size of the findings.

Nandish [00:12:43] There's a second workflow for the individual radiologists in that second workflow where the individual radiologist will be need to upload the images to the solution what we have. So it will be de-identified, it will run through our anonymization tool and it will be uploaded to the solution and the Ask AI will be worked on that. And after that the workflow is same. So these are the two different workflows. What we have come up with, where it can fit for the hospitals or for the individual radiologist.

Tony [00:13:14] And when we talked about how Intel has partnered with LTTS obviously Intel where we care about making things faster, more efficient in terms of technology. So can you talk a little bit about how Intel's OpenVINO Toolkit and AI Analytics Toolkit has helped you guys deliver a solution, a quality solution, to your customers faster?

Nandish [00:13:37] Yeah, when we speak about the AI solutions, right? So most of the things, what we consider is the inference time when it does more of deep learning based on the images in the frames, one is the inference time, next is the turnaround time and also the size of the AI model. So the Intel OpenVINO has helped in optimizing the inference pipeline by reducing 75% of the turnaround time. And also the model size has been reduced by 36% and also the inference time has been reduced by 49%. So that is how the OpenVINO has contributed and reducing most of our time, the model size and the turnaround time where it is optimized for use with Intel processors.

Tony [00:14:32] And you mentioned the turnaround time and you said the turnaround time is a lot faster. What is that turnaround time? Is that the turnaround time for you to create and optimize a new model? Is that turnaround time for customers to get the results? What does that look like?

Nandish [00:14:46] Turnaround time with respect to the result, with respect to the process time where the doctor looks to start looking at the image and then he will identify the findings and then he will start reporting it. So from the beginning of the image to the reporting of that particular cases where that time has reduced to 75%. So that is a turnaround time what we are talking about. When we speak about time when taken by the doctor, then obviously it will reduce as the waiting time of the patient.

Tony [00:15:19] Okay, great. So I'm going to get basically I'm going to get my results in only 25% of the time as I would have had before, is kind of what you're saying?

Nandish [00:15:28] Yes.

Tony [00:15:29] That's fantastic.

Nandish [00:15:31] And also, I can say that when we speak about turnaround time, let me look into the all inference pipeline. Very by using Intel OpenVINO, it has been made us 1.84 times faster.

Tony [00:15:43] Can you talk about why targeting X-rays is important versus some other type of diagnostic tool?

Nandish [00:15:48] Yeah, because as I initially spoke, right, the huge volume of X-ray just X-ray images are populated and over the most of the cities don't have that many number of radiologists in place to report it faster. And X-rays are an easily available mortality in every cities. There's not like a CT or MRI where they need to travel or go far to get it done. X-ray is very much handy where the patient or the patient that persons can reach out to. Also, the any doctors will first go with the X-ray investigation before asking the patient to go for CT or MRI. So X-rays the first investigation to do the diagnosis.

Nandish [00:16:29] So hence the volume of X-ray images are more and other reporting time should also be quicker so that patient can be referred for further investigation because on the X-ray images. So this is itself take more time then obviously it will affect on the further investigations where the patient need to undergo.

Tony [00:16:47] It sounds like you guys have an end to end pipeline to enable radiologists, are there other competition solutions that you guys have looked at, and how does your product compare versus what they are providing?

Nandish [00:17:07] See, we compare with one of the solutions where the number of images used for training, right? So we have 50,000 and then use 1.5 lakhs or two lakhs images. With the 50,000 images, we are having a better accuracy, if we are further, if we get more data and if we train the model on that, obviously, well, the accuracy level will be higher. So with the minimum required dataset, we have reached across this accuracy what we have presently. And as I said this, along with the annotations, it also make the doctor if our solution is not some findings. So it will make the doctor to do the annotation manually and the doctor report with the new annotations which are done so in these cases. So there is a discrepancy, right? So this discrepancy will be considered as that image, as a retouch image. Once this retouched images reaches the 50,000, then the model will be retrained again. Once it is retrained, so we'll look into the accuracy or other metrics if it is better, then this model will be replaced by the existing one. So that is how the self training capability, what our solution is. So for this discrepancy, we consider the report as a ground truth.

Tony [00:18:28] Okay, that's great. So you're continually fine tuning this based on the radiology, sorry, the radiologists feedback to provide better solutions for for really better outcomes for your patients.

Nandish [00:18:39] Yes.

Tony [00:18:40] All right. Well, I think that ends our time for today. I'd like to thank Dr. Nandish for joining us and talking to us a little bit about the Chest-rAi radiology solution. So thank you, Doctor Nandish.

Nandish [00:18:52] Thank you. Thank you, Tony. Thank you for the opportunity.

Tony [00:18:56] And thanks to you, our listeners, for tuning in and learning a little bit more about Chest-rAi and how it helps doctors and patients. And also health products like Intel's OpenVINO and the Intel AI Analytics Tool kit can accelerate important AI solutions in the real world. Until next time when we talk about more technology and trends in industry.