



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 15, Issue 4, April 2026

Object Detection using Mask R-CNN for Tumour Detection

Sayali D. Chavan¹, Pranav P. Barbade², Aniket S. Gujare³, Pragati U. Sable⁴, Harish A. Jagle⁵

Mentor, Department of Artificial Intelligence & Machine Learning, AISSMS's Polytechnic, Pune, Maharashtra, India¹

Student, Diploma in Artificial Intelligence & Machine Learning, AISSMS's Polytechnic, Pune, Maharashtra, India²⁻⁵

ABSTRACT: Picture checking by computers helps find cancer spots faster than people staring at scans. Machines used to miss tricky details, but now they catch more because smart software learns from tons of examples. Doctors once spent hours reviewing each image, risking tired eyes and mistakes. New tools built on deep learning spot odd growths without getting bored or distracted. These systems grow sharper over time, reducing slips that happen when humans work alone.

Something different happens here - a tool built on artificial intelligence spots tumours in medical scans. Not every method works like this one does; Mask R-CNN picks out shapes while outlining where they sit in the image. Instead of just naming areas, it draws around them with precision. Medical pictures, whether from MRIs or CT devices, go into the process quietly transformed through analysis. What comes out includes marked zones showing possible growths, shaped exactly like what lies inside. The machine doesn't guess - it learns patterns and applies them frame by frame. Looking at the outcomes, Mask R-CNN handles tumour detection with solid precision. Helping doctors work quicker, it cuts down hands-on tasks during diagnosis. Instead of traditional methods, this approach uses deep learning to analyze medical images smartly. Through computer vision, the project brings a practical tool into real-world health settings. While focused on imaging, its impact lies in making complex analysis more manageable.

I. INTRODUCTION

Spotting tumors ranks among the top uses for analyzing medical pictures in health care. Growth of unusual cells in the body defines what a tumor is, often dangerous unless caught soon. MRI and CT scans help physicians see these growths hidden within organs and tissues. Yet examining those images by hand demands skilled eyes, slowing things down noticeably. Big volumes of visual patient data make the task stretch even longer than expected.

Lately, artificial intelligence has been moving fast. Because of this shift, spotting tumors automatically now draws more interest. Picture recognition got a boost when deep networks started doing well. These systems handle visuals with surprising skill - finding items inside scans, sorting them, even outlining shapes. One standout approach does two things at once: it marks areas and cuts out exact parts. That method? It goes by Mask R-CNN. Medical pictures benefit because tumor zones show up clearer than before. Precision improves when the model highlights exactly where trouble might be. Years back, such detail felt out of reach. Now, results come quicker, sharper.

A clearer picture emerges when the system outlines tumours with precise borders instead of rough estimates. What happens next is a detailed mask forms, showing exactly where the abnormal tissue spreads across the scan. Doctors find it easier to judge location because shapes appear without guesswork. Decisions gain confidence since visual guidance comes straight from pixel-level analysis. Effort drops sharply once repetitive tasks run on their own. Mistakes fade as machines spot what humans might overlook during long reviews. Early signs become visible earlier thanks to consistent pattern tracking over time. Healthcare workers gain room to focus on complex cases rather than routine checks.

This project builds a smart tool to find tumors by applying the Mask R-CNN method. Medical scans go into the system, then get analyzed through advanced neural networks. What comes out are clear markings where tumors appear in the images. Instead of guesswork, it shows exactly where problem areas lie. Through real testing, it proves artificial intelligence fits well inside medical workflows. Accuracy matters - this approach delivers consistent results when examining complex scans. Learning patterns from data helps spot what human eyes might miss. With enough training,

the model adapts to different cases without constant oversight. It runs on logic shaped by examples, not rigid rules. When tested, outcomes stayed stable across varied inputs. Such systems open paths toward faster diagnosis in hospitals. They work quietly but change how decisions are made behind the scenes. Not magic - just careful design meeting practical needs. Over time, small improvements add up to meaningful impact. This one focuses only on tumors, yet points to broader uses later. Each step forward relies on repetition, refinement, patience.

II. PROBLEM STATEMENT

Spotting tumors through medical pictures like MRIs or CT scans plays a key role in figuring out what's wrong. Looking closely at these visuals helps physicians find unusual growths within the body. Still, going over each image by hand often takes too long, sometimes misses details, particularly if the mass is tiny or oddly shaped. Skill level matters - more seasoned professionals tend to see things others might overlook. Reviewing many scans without help piles up stress and effort for healthcare workers.

Some medical scans show blurry spots because unwanted speckles crowd the view. Tumours sometimes blend into surrounding tissue, hiding their edges. When shapes lack clear outlines, figuring out how big they are gets tricky. Old-style software tools struggle to measure these fuzzy areas right. What appears on screen might not reveal where growth really stops.

A smart tool must spot cancer areas fast without mistakes. Because they learn patterns well, systems like Mask R-CNN do solid work finding objects and cutting out shapes in pictures. Instead of guessing, the new setup uses artificial thinking to scan health scans, marking problem spots by itself. Fewer people hours are needed when machines assist - accuracy climbs while physicians get quicker results during checks.

Project Goals

Primary Objectives:

A system that spots tumors could run on artificial intelligence. Deep learning methods might shape how it works. The goal is building something smart enough to catch abnormalities early. Learning patterns from medical images becomes its main task. Detection improves when models train on varied examples. Machines start recognizing what looks wrong after enough exposure.

Start by applying the Mask R-CNN method so tumours can be spotted clearly while separating them visually in scans. The model runs through images, pulling out regions where growths might hide. From there, shapes get outlined pixel by pixel using learned patterns. Detection sharpens when overlapping areas are refined across multiple passes. Each output includes both location and a detailed mask tied to tissue type.

Finding cancer areas in pictures taken by machines like MRIs or CT scanners.

A bright outline shows where the growth sits, making it easier to see. The marked zone helps spot details fast, drawn clearly around irregular shapes. What stands out gets framed by a thin layer, set apart from nearby tissue. Where color stops matches exactly what lies beneath, shaped to fit each edge.

- To improve accuracy and efficiency of tumour identification.

One reason is cutting down on hand work when checking medical scans.

A doctor might spot problems faster with help from a smart tool. This setup aims to back up medical judgments using technology. Instead of replacing professionals, it adds another layer of support during checkups. The goal shows up in how results get cross checked for accuracy. Through digital assistance, decision making could become more reliable overall.

A user opens the system to add scans, then sees outcomes displayed plainly. Uploading happens first, after that findings appear without delay. Pictures go in one way, information comes out another. The screen stays clear during transfers, responses follow right after. Input leads directly to output, no extra steps stand in between.

Secondary Objectives:

- To preprocess medical images for better model performance.

Looking at how an image feels to the eye - its roughness, form, spots that stand out. Checking curves and edges where things seem off or irregular. Patterns that do not match typical structures get close attention. Odd areas show up when comparing usual versus unusual layouts. Details like lumps, spikes, or blurred zones matter most here.

- To improve early detection of tumour using artificial intelligence.
- To demonstrate the use of deep learning in healthcare applications.
- To build a reliable and efficient tumour detection model.

III. LITERATURE REVIEW

Spotting items in pictures along with dividing images into parts plays a big role in how computers see, especially when looking at medical scans. Long ago, basic ways like setting limits, finding borders, or pulling out key details helped locate things inside visuals. Still, those approaches struggled when faced with tricky health-related photos since tumor shapes, dimensions, or brightness levels often change unpredictably.

Because machine learning evolved, deep learning began powering tools that spot things in pictures. Out of those tools, convolutional neural networks stood out over time. These networks grab key details like lines and surfaces straight from photos without human help. Spotting those pieces makes identifying what is inside an image more reliable. In medicine, scientists turned to these designs when sorting scans or hunting abnormal growths.

Picture sections get spotted better thanks to systems like R-CNN, its faster version, and the one after that. Boxes drawn around items in photos became more reliable over time because of how these approaches narrow down areas first. Still missing was a sharp outline exactly matching each item's edge shape.

Here comes a smarter version of Faster R-CNN - Mask R-CNN tacks on a mask-predicting stream. Instead of just spotting items, it outlines each one down to the pixel. Picture this: every blob gets its own precise border drawn around it. Because of that edge, doctors see tumours more sharply in scans. Sharp edges mean less guesswork when measuring growth zones.

A new study finds Mask R-CNN works effectively for spotting brain tumours, identifying lung nodules, also separating cancer cells in medical scans. Tiny details and uneven forms are picked up clearly by this system, making it fit for finding growths. Because precision runs high and shape outlining is strong, hospitals often apply this tool when using image analysis software.

Deep learning models for spotting objects tend to outperform older image methods, based on what studies show. Accurate detection and separation of tumors? That's where Mask R-CNN shines - making it the pick here.

IV. PROPOSED SYSTEM

Something unusual happens when images meet code - a quiet shift unfolds inside MRI and CT data. Instead of human eyes spotting irregularities, software steps in silently. This setup leans on Mask R-C-C-N-N, a form of deep learning that sees shapes where others see noise. It does two things at once: finds odd areas, then draws precise outlines around them. These outlines are called segmentation masks. They give doctors clearer views without guesswork. Detection becomes less about searching, more about confirming what shows up. Accuracy shifts because the machine learns patterns people might overlook. Medical review gains something steady, repeatable. What used to take minutes now takes seconds. A different rhythm enters diagnosis. Clarity grows not from speed alone but from consistency.

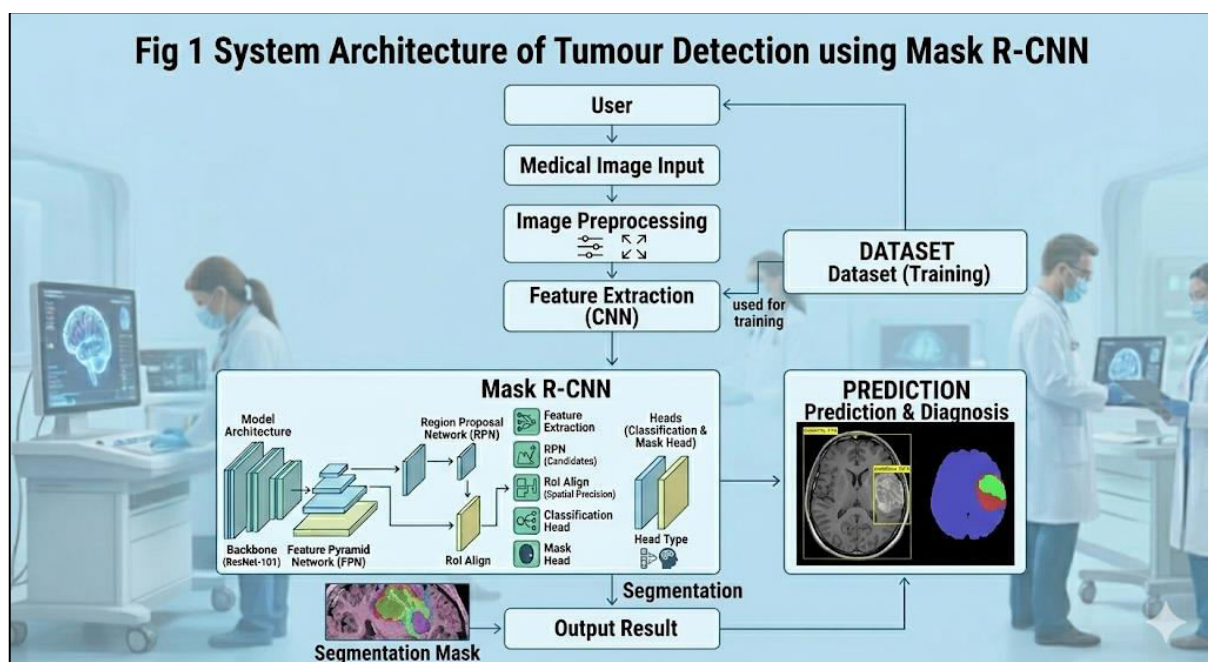
A digital platform takes in medical scans right at its entry point. After arriving, each picture gets adjusted - resized, balanced in tone, cleaned of static fuzz. Quality shifts happen here, quietly setting things up ahead of time. Once tuned, the visual data fits better with how smart algorithms need it structured.

Once cleaned up, the picture moves into the Mask R-CNN system. Inside, a series of layered networks pulls out key details from the scene. A built-in detector scans for spots that might hold tumours. Those areas get labeled while outlines are drawn tightly around each suspected mass.

Highlighted spots show where tumours might be, sitting right over the scan like clear markers. A doctor can see how big it is, what form it takes, plus exactly where it lies within the body. Errors drop because the tool sharpens precision while cutting down time spent by hand. What once took minutes now appears almost instantly, layered neatly across the image.

A fresh look at how tools might work in hospitals shows promise for spotting growths sooner, aiding studies, also supporting software that helps doctors decide. Built without excess, it runs fast, grows when needed, fits right into checking scans where speed matters.

V. SYSTEM ARCHITECTURE



Description:

Structure of the tumour detection setup gives a clear view of its parts and how they connect. Built on deep learning methods, this approach finds abnormal growth areas in scans like MRI or CT. Starting with image entry, data moves into cleanup steps before key traits are pulled out. After that, the Mask R-CNN engine works through the details to mark possible tumours. Finally, outcomes appear in a visual format ready for review.

Up top, someone shares a medical scan using the web interface. Once it arrives, the system shifts into prep mode - adjusting size, balancing tones, getting things ready. This cleanup step sharpens the picture just enough. Because of that, the neural network can make better sense of what it sees.

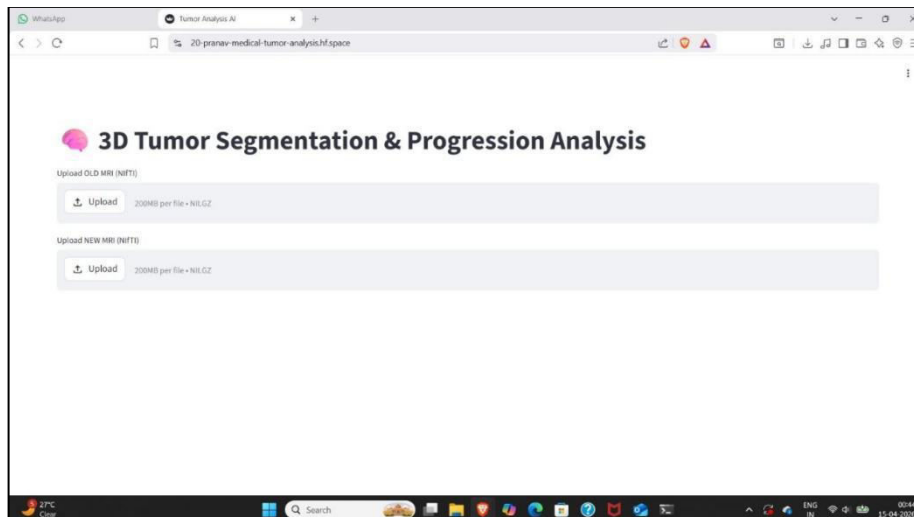
Once cleaned up, the picture moves into the Mask R-CNN system. From the medical scan, key details emerge through a deep learning network. Potential tumour spots show up when the Region Proposal Network scans the frame. These found areas get labeled while outlines form around each growth zone.

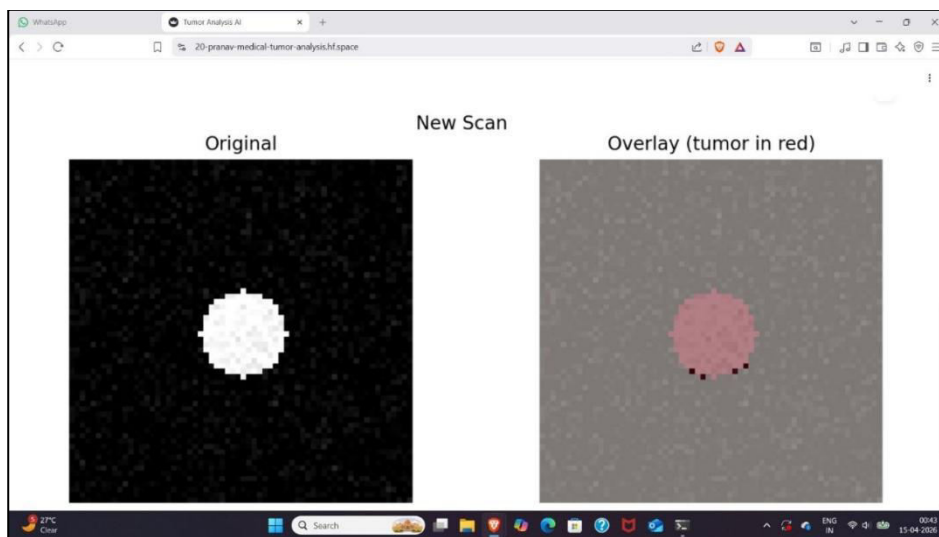
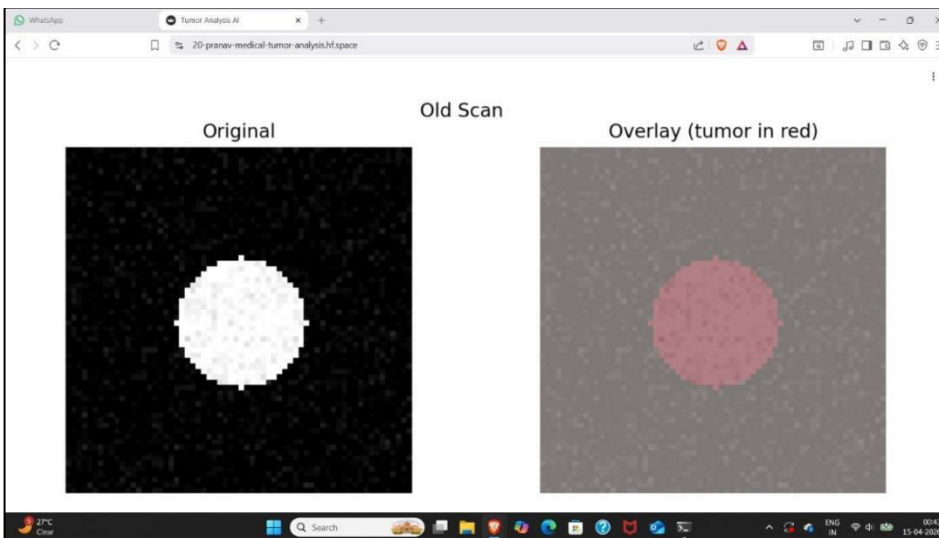
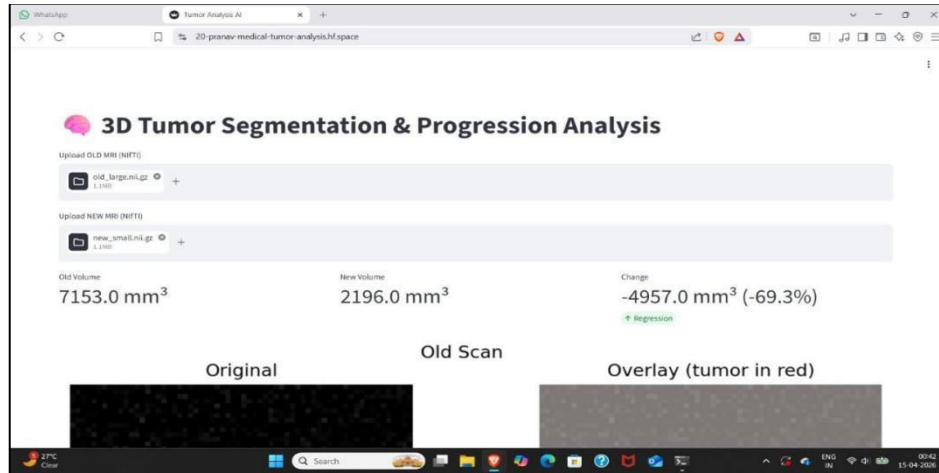
Out of the processing stage, data moves into the output unit, here the tumor section appears overlaid on the scan. Showing up clearly, the identified tumor zone comes with a segmented outline, giving clearer insight into its position and shape. Built this way, the framework handles medical scans quickly while delivering precise detection outcomes.

VI. METHODOLOGY

1. Data Collection Begins
A collection of medical scans - like MRIs or CTs - showing both tumours and healthy tissue comes from trusted providers. From these examples, pattern recognition in abnormal growths begins to take shape inside the system.
2. Data Preprocessing Step Two
After gathering the pictures, each one gets adjusted in size and balanced for clarity. This cleanup step makes it easier for the system to study them closely.
3. Image Input Step Three
A file shows up from the person using the tool. Once inside, it moves straight into a model that has already learned what to look for.
4. Feature Extraction Step Four
A pattern-finding system picks out key details in a scan - like lines, forms, or odd-looking areas. What it sees depends on how the layers process each section of the picture.
5. Region Proposal Network
A section of the picture might hold a tumour - that is what the RPN picks out.
6. Mask R CNN detection step six
A small part of the image gets labeled by the system once it spots something off. Tumour zones then show up clearly through a shaded overlay drawn around them.
7. Prediction Result
Out of nowhere, a result appears - either tumour found or image looks clear. Sometimes it's one, sometimes the other, depending on what's seen inside.
8. Final Results Shown
A bright spot shows where the tumor is, marked clearly on the picture.

VII. RESULT





VIII. CONCLUSION

This study built a smart tool using Mask R-C-C-N-N to spot tumors in medical pictures. Not only does it work on MRIs, but also on CT scans - finding abnormal areas with solid precision. Instead of just marking where growths appear, the method outlines their shape sharply. Because it combines detection with fine segmentation, boundaries stand out clearly. Accuracy improves when locations and edges are handled together through one network.

Deep learning proves useful when studying tricky medical scans, while also spotting odd areas in tissues. Instead of relying only on human eyes, the tool speeds things up by cutting down hands-on work. Tumour zones get picked out clearly thanks to Mask R-CNN, which draws precise outlines around them.

Looking at how tech shapes medicine today, one thing stands out - artificial intelligence plays a key role in health-related tools. Doctors might find help through this new setup when figuring out diagnoses, which could lead to sharper choices. When tested, it showed that systems like Mask R-CNN handle tumour spotting well, proving their worth where actual patient scans are involved. What ends up mattering most? Real results in messy, everyday hospital settings.

REFERENCES

- [1] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," IEEE International Conference on Computer Vision (ICCV), 2017.
- [2] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.
- [3] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," Springer, 2015.
- [4] G. Litjens et al., "A Survey on Deep Learning in Medical Image Analysis," *Medical Image Analysis Journal*, 2017.
- [5] J. Redmon et al., "YOLO: Unified, Real-Time Object Detection," IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.
- [6] PyTorch Documentation. Available: <https://pytorch.org>
- [7] TensorFlow Documentation. Available: <https://www.tensorflow.org>
- [8] OpenCV Library Documentation. Available: <https://opencv.org>
- [9] Kaggle Medical Image Dataset. Available: <https://www.kaggle.com>
- [10] Research papers on tumour detection and medical image processing from IEEE Xplore and Google Scholar.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details