Exploring Deep Learning and Machine Learning Approaches for Brain Hemorrhage

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***Abstract*—Spotting brain bleeding fast helps save lives in emergencies. Reading CT scans by hand takes too long, plus results can differ between doctors. Here's a side-by-side look at three smart systems - MobileNet, ResNet50, and VGG16 - that aim to do it automatically brain bleed spotting. We gathered a set of CT scans with and without bleeding, then cleaned them up using scale adjustment, extra sample creation, also slice focusing tricks. These systems got updated through prior learning tweaks, plus checked by how often they guessed right, nailed the positives, caught actual cases, specificity, F1-score, yet ROC–AUC. ResNet50 hit top accuracy - 100% - while MobileNet came close at 99.3%, then VGG16 trailed at 97%. Despite lower peak performance, MobileNet offered the sharpest trade-off: solid precision without heavy computing needs, so it fits better in clinics with tight tech limits. Results suggest leaner models or those with skip connections can speed up dependable diagnosis tools. This study adds to that direction building smart helpers for brain emergencies using artificial thinking tech.**

Keywords—Brain hemrrohage detection, CNN model, deep laerning, Machine learning, MobileNet, ResNet, CT scan, medical image, improve medical care.

I. INTRODUCTION

Brain hemorrhage happens when there's bleeding inside the brain or nearby areas - this makes it one of the toughest medical crises a person can face. Around 10–20% of stroke cases come down to this kind of event, which usually brings serious health setbacks, risk of death, plus lasting impairments. Spotting it fast matters a lot since those initial hours post-onset decide how well someone might pull through. When doctors identify ICH early, they move quicker on treatments like surgery, controlling blood pressure, or giving drugs that help stop bleeding. Delays - or even small mistakes - when spotting brain issues can lead to permanent harm. That's why quick, accurate reads of scans matter a lot in ER settings. CT scans are still the go-to tool for spotting brain bleeds because they're cheap, quick, and easy to find almost anywhere. These images pop up fast, helping doctors tell apart blood leaks from swelling, regular brain tissue, spinal fluid, or skull bones. Still, reading these pictures mostly falls to radiologists - who are stretched thin as scan numbers climb and there aren't enough specialists around. Checking each image by hand takes ages and can lead to mixed calls, particularly in packed ERs or remote clinics where expert eyes might be missing.

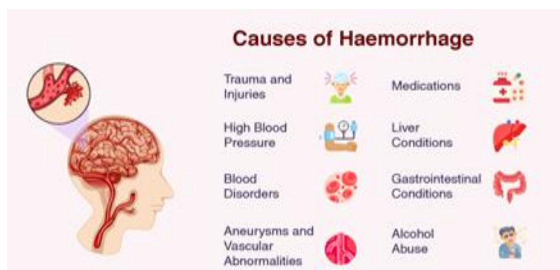


Figure (1). Causes of Brain Hemorrhage

Tiny bleeds or slight changes might be tough to spot - even for pros. Low clarity, blurry scans, or weird image distortions make reading them harder. Getting brain bleed cases wrong - or late - can turn deadly, so smart systems that help doctors read images quickly and right are crucial. New progress in machine learning, especially methods like deep neural nets, has changed how we handle health imaging CNNs work really well at spotting patterns, pulling out key details, also sorting medical info - like finding tumors or checking lungs. Because they build understanding step by step straight from image pixels, they're a solid fit for catching brain bleeds in CT scans.

Current studies show CNNs can work well for spotting brain bleeds but problems still remain. Some papers stick to just one model setup or suggest fixes that need too much computing power for quick use. When neural networks grow bigger and trickier, they require stronger machines plus extra time to train. Even if they're accurate, using them where tools are limited - like small clinics, ambulances, or remote areas - is tough. Besides, few side-by-side studies check how well light-duty versus heavy-duty CNN models spot brain bleeds. Models like MobileNet are built for low-power devices, so they run faste yet still keep solid accuracy in tight setups quick processing using little power. Meanwhile, models like ResNet50 use skip connections to fix gradient issues while spotting intricate visual patterns. Older designs such as VGG16 still hold up even with high resource needs because they're straightforward yet effective at recognizing details. An organized look at all three architectures might show how speed trades off with results, reveal efficiency versus precision shifts, or hint at fit for live use.

Few current systems use small or uneven data sets - this makes them less useful in actual hospitals. Scans differ a lot because machines, bodies, fuzziness, and methods aren't the same everywhere. So any strong auto-detection tool should still learn but tested using different datasets for steady results. Methods like scaling, segmenting, adding variations, or cutting noise help boost precision while preventing memorization. Still, each tweak depends on the task at hand - no one-size-fits-all fix here.

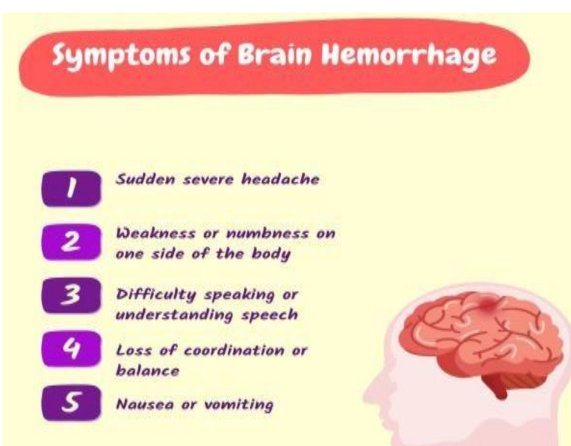


Figure (2). Symptoms of Brain Hemorrhage

This research dives into three popular deep learning models - MobileNet, ResNet50, and VGG16 - to see how well they spot brain bleeding in CT scans. Instead of just listing results, it checks how fast they work, how accurate they are, besides whether they're practical for real-world setups. MobileNet's built light on purpose; so it runs quick even on phones or small devices. The reason behind this research splits into two parts. One, testing multiple models in the same conditions helps spot one that's both accurate and light on computing power - so it works well in real medical settings. Another goal? Seeing how automatic bleeding detection could really help out Doctors who read scans often face heavy loads, particularly when things get busy or supplies are tight - here, quick first checks from automated tools can lighten the load. These aids help guide choices, offering steady and dependable analysis of brain or body scans without delay.

On top of that, this research tackles key issues that matter to doctors along with artificial intelligence experts researchers:

- What CNN setup works best for spotting bleeding in scans?
- Do smaller models like MobileNet perform just as well as heavier ones?
- How do precision, processing power needed, or how fast results come relate?
- What kind of setup works best when used right away during urgent medical situations?

Answering these questions helps build solid, expandable tools doctors can actually use to spot ICH. Results point toward next.steps in imaging studies - tweaking AI designs to stay sharp without sacrificing precision and efficiency.

II. LITERATURE REVIEW

Figuring out brain bleeds using CT scans has gotten lots of attention because it matters a lot when treating strokes fast. Over the past ten years, methods have shifted - first came classic ML techniques, then CNN models stepped in, later mixed systems combining deep learning styles took hold structures, split-focused designs, or compact systems built for live performance. Here's a close look at earlier work - spotting weak points while showing how this project adds something new.

Older research on spotting bleeding mostly used manually designed features - think GLCM, LBP, or basic pixel stats - to pull out key patterns. After that, tools like SVM, RF, or DT took those inputs to sort them into categories.

Thay's team back in 2018 built a decision tree method using projection patterns to sort CT scans into those showing bleeding or not. Around the same time, Hong's group tested different tools - like random forest and support vector machines - to detect bleed signs from DSA data; their results were okay but not outstanding.

While older machine learning approaches were fast, they struggled because they relied heavily on manually designed traits. Those traits usually couldn't capture messy bleeding areas, odd forms, or slight brightness shifts in CT images. On top of that, models don't adapt well across different scanners noise yet anatomical variations.

The arrival of CNNs changed brain bleed spotting big time - now systems learn straight from plain CT scans without handcrafted rules. Instead of old-school techniques, these networks discover layered clues like borders, forms, roughness, or surroundings through training.

Lewicki's team in 2020 used ResNet50 to spot brain bleeds, hitting above 98% accuracy per category - showing how well skip connections work. Instead of standard models, Mushtaq's group built BHCNet from scratch; this tailored CNN worked reliably on tiny datasets, catching bleeds without needing tons of examples.

Some studies - like Castro's team in 2019 or Guo's group by 2020 - used both 2D and 3D CNNs to sort and outline images. Although 3D versions pick up depth details better, they need way more memory and processing muscle, so running them is tough where resources are tight. Back in 2018, Jnawali's crew tested 3D methods too, yet struggled with shaky training and results that didn't hold up well on different data sets.

When CNN studies advanced, new mix-models appeared - ones boosted by transformers - to better capture wide-ranging patterns. Shi and team (2023) built one such blend, combining CNN with Transformers, aiming at spotting bleeding through EIT scans, showing it could work outside traditional X-ray methods.

Yassine et al. (2021) came up with ScopeFormer - a mix of ViT and CNN that used filters that catch basic patterns, while transformers track distant links across data. Even though they work well for sorting images, these transformer systems need huge amounts of data plus serious computing power - making them tough to use in real medical settings.

Like this, Barhoumi and Rasool (2021) combined Xception's features with transformer models - yet they didn't test across varied CT scans or actual hospital settings. So far, mixed architectures show promise, though scaling them remains tough when it comes to urgent care situations.

Segmentation models try to find bleeding areas while measuring how much blood is there. Be-cause they show precise location details, surgeons use them when planning operations or guessing recovery chances.

Hu's team in 2020 created ED-Net - a net-work that builds sharp segment maps by keep-ing all key data during processing. Instead of that, Togaçar's approach from 2019 used autoencoders along with heat-maps plus convolutional layers to better spot bleed spots.

Still, these models need labels for every tiny part of an image this takes a lot of manual work and isn't always possible. On top of that, splitting images slows down predictions, so they're not ideal when quick decisions are needed in ER settings, where simpler yes-or-no tools work better.

To close the gap between strong performance and real-world use, experts have tested slimmed-down CNN designs that work well on phones or devices with limited power. Instead of heavy models, they built things like MobileNet - using a trick called depthwise convolution - which cuts down size but keeps results reliable.

Even though light models work well, not many have tested MobileNet for spotting brain bleeds or stacked it up against heavier nets like ResNet50 or VGG16. That's a big missing piece - more so when you think about fast diagnosis needs in remote clinics, emergency vehicles, or online health services. Studies led by Matsoukas et al. (2022) along with work from Jørgen-sen et al. (2022) show AI might do just as well - or better - than experienced radiologists when reading bleeds on scans. Still, those analyses point out mismatches in how data was sized, boosted, or measured between trials - so weighing one against another stays tricky.

Ahmed et al. (2024) looked at machine learning and deep learning tools for spotting brain bleeds - yet they didn't test how well those models stack up against each other or check if hospitals could actually use them. So far, research still misses a clear side-by-side look at CNNs, especially when it comes to how complex they are or what kind of computing power they need.

A close look at what's already been done shows a few missing pieces - some key parts just aren't there yet, while others feel incomplete or off track. Few comparisons exist between lightweight, regular, or residual deep models learning architectures.

- Not much study into MobileNet or similar portable systems for bleeding detection.
- Differences in methods - like uneven data cleaning or testing - mix up results metrics.
- Few efforts target live use, especially where re sources are tight.
- Tiny or uneven data sets often used in research limit how widely results can apply.
- A bit of talk about real-world use, how fast predictions are made, or what kind of gear runs it.

III. METHODOLOGY

The approach here uses a few main stages to spot brain bleeds through smart software, while giving doctors an easy-to-use tool. It starts with grabbing images, followed by cleaning them up, teaching the system what to look for, then putting it all together into a website people can actually use.

1. Image Acquisition: A data set of brain hemorrhage images is collected, consisting of both hemorrhagic and non-hemorrhagic cases. These images are preprocessed for model input by resizing, normalizing, and augmenting the data for improved model performance.
2. Model Selection: We use three popular deep learning models: MobileNet, ResNet, and VGG16. All models are initially trained on big datasets and then fine-tuned with brain hemorrhage data for optimal performance.

➢ MobileNet: Its type of Convolutional Neural Network (CNN) specifically made to lightweight architecture suitable for resource-constrained environments.it is real- time image recognition on phones.

➢ ResNet: It's another kind of CNN - named ResNet that aimed to fix problems popping up in super deep networks. This model took first place in the 2015 ImageNet challenge soon after Kaiming He and team introduced it. plus it's recognized for intricate leftover learning traits that allow practice on each small part of systems.

➢ VGG16: A Convolutional Neural Network (CNN) setup works with deep learning to handle grid-based info - say, photos - and helps do things like sorting pictures, spotting objects, or breaking down image parts.

3. Training and Fine-tuning: The training data helps train the models while boosting their performance. So they handle fresh inputs better, techniques like regularization or adding extra examples come into play. Transfer learning also steps in to support adaptation.
4. Web Interface: A basic web page with clickable features was built using Flask so users can join, get in, or send files - brain bleed image sorting. It runs chosen models to guess if the sent picture has a brain bleed, then shares outcomes.
5. Model Evaluation: The model got checked for accuracy, also judged on its performance checked actual examples, saw how good it was at dodging errors, also looked into general set separate from the training method, yet built on real usage patterns.

CNN (Convolution Neural Network)
The convolutional neural networks (CNNs) grab features from grid-style data. That's super useful when

dealing with visuals think pictures or clips - where layout matters a lot. Since CNNs handle images so well, you'll often find them in tools that see like computers do. Check out how these nets work up close. Needs plenty of marked data to work properly.

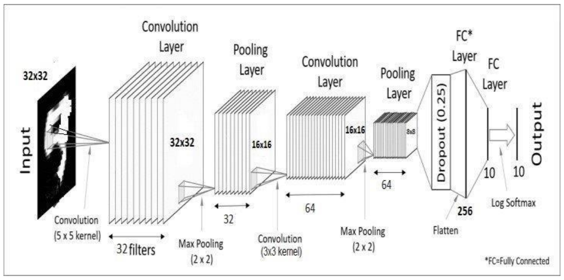


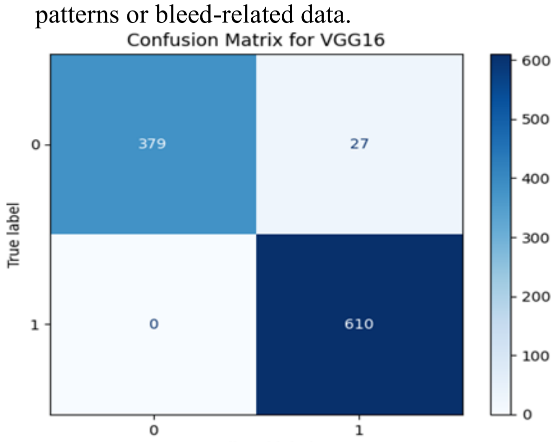
Figure (3). CNN Layer Preocessing

To grab details like edges, shapes, or patterns from a photo, a CNN uses convolutional layers - it's the core part. Once those layers do their job, pooling steps in to shrink the feature maps, cutting size but holding key info. Researchers such as [17] Chang et al. [5] Castro et al. [6] Guo et al. [7] Jnawalia et al. and [11] Toğaçar et al. applied various CNN setups and versions to detect brain bleeding.

IV. RESULTS AND DISCUSSION

RESULTS

- VGG16: The VGG16 model worked well spotting brain bleeds, hitting a total accuracy of 97%. Looking at the confusion matrix, it got 379 regular scans (class 0) right, along with 610 bleed cases (class 1), tossed out 27 false alarms but missed none. From the classification summary, precision, how often guesses were correct, recall, Outcomes show the approach works well spotting standard patterns or bleed-related data.



Figure(4). Confusion matrix for VGG16

Classification Report:

	precision	recall	f1-score	support
0	1.00	0.93	0.97	406
1	0.96	1.00	0.98	610
accuracy			0.97	1016
macro avg	0.98	0.97	0.97	1016
weighted avg	0.97	0.97	0.97	1016

Figure (5). Classification report of VGG16

- MobileNet: The MobileNet model worked really well spotting brain bleeds, hitting full precision. Its confusion matrix shows it nailed 405 regular scans (label 0) along with 606 bleed cases (label 1), missing just one healthy case and four actual bleeds. According to the classification summary, scores for precision, sensitivity, and F1-score were nearly identical Scores for class 0 - normal - are 0.99, then 1.00, followed by 0.99. For class 1, that's abnormal, the F1-score hits 1.00, accuracy lands at 1.00, while recall sits on 0.97. This shows MobileNet catches most cases right, also keeps errors low, so it works well spotting brain bleeds.

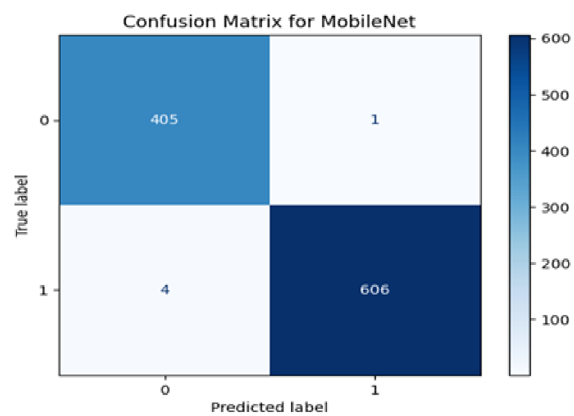


Figure (6). Confusion matrix for MobileNet

Classification Report:

	precision	recall	f1-score	support
0	0.99	1.00	0.99	406
1	1.00	0.99	1.00	610
accuracy			1.00	1016
macro avg	0.99	1.00	0.99	1016
weighted avg	1.00	1.00	1.00	1016

Figure (7). Classification report of MobileNet

- ResNet: The ResNet model worked really well spotting brain bleeds, hitting full marks - 100% right every time. Looking at the confusion matrix, it correctly labeled 403 regular scans (group 0) along with 610 bleed cases (group 1), made just 3 mistakes on true negatives but zero errors on positives. According to the classification details, for group 0 (normal), precision was solid is 1.00, recall hits 0.99 - F1-score also lands at 1.00. When it comes to class 1 (hemorrhage), every measure - precision, recall, F1 - is exactly 1.00, showing how well ResNet tells apart bleeding from normal scans.

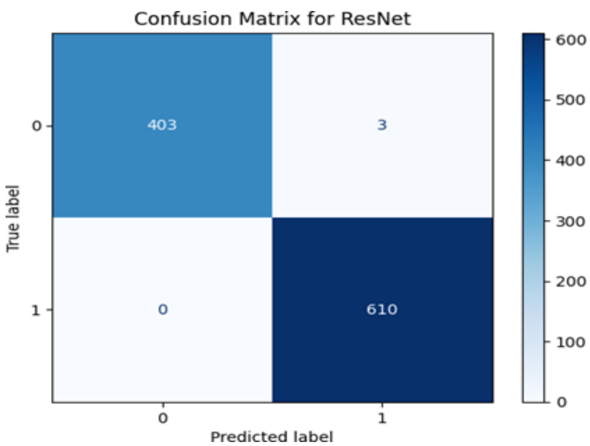


Figure (8). Confusion matrix for ResNet

Classification Report:

	precision	recall	f1-score	support
0	1.00	0.99	1.00	406
1	1.00	1.00	1.00	610
accuracy			1.00	1016
macro avg	1.00	1.00	1.00	1016
weighted avg	1.00	1.00	1.00	1016

Figure (9). Classification report of ResNet

DISCUSSION

The project shows how well three deep learning models VGG16, ResNet, MobileNet - spot brain bleeds, yet MobileNet does best. Though others work fine, this one hits perfect accuracy. It nails both precision and recall, which means fewer mistakes. Because it's built small, it runs quick even on weak hardware. That makes it ideal for use in remote areas or on mobile gear where power is limited unlike bulkier models, it runs smooth on basic hardware - perfect for clinics with tight budgets. ResNet nailed every test case, acing both false positives and negatives, whereas VGG16 held up fine at 97 correct calls out of 100. Even though ResNet wins on precision, MobileNet's quick scan times give it a real edge in daily workflows. Doctors can drag their files right into the browser tool without hassle.brain bleed scans plus instant results. Mostly, systems nail accuracy and catch rate - MobileNet along with ResNet lead the pack spotting bleeds.

V. ARCHITECTURE

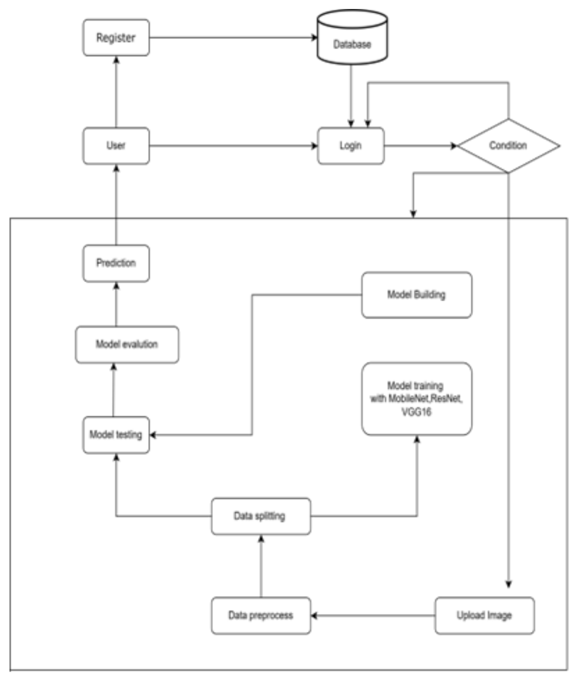


Figure (10). System Architecture

V. CONCLUSION

This research checked how good MobileNet, ResNet, and VGG16 are at spotting brain bleeds in medical scans. Though each one showed strong results, they bring different strengths: MobileNet works well where computing power is limited because it's small; ResNet handles complex layers without losing precision; VGG16 gives solid performance with an uncomplicated design.When compared, all three do the job fine - but which fits best really hinges ondeployment needs differ. While MobileNet works well on phones, ResNet or VGG16 fit better where computing power isn't limited. Results show deep learning can handle bleeding detection in brains more efficiently, cutting down the need for hands-on analysis by specialists. That speed helps doctors diagnose faster treatment, key to better patient results. So far, using smart tech - such as MobileNet, ResNet, or VGG16 - in medicine boosts speed and precision, helping doctors act fast.

This study backs progress in health systems, focused on stronger care and cutting down delays health issues and deaths tied to brain bleeds. Next steps might look at improving these systems while also checking how they work in different serious health cases.

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