iJRASET
International Journal For Research in Applied Science and Engineering Technology

# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

**Volume:** 14 **Issue:** V **Month of publication:** May 2026

**DOI:** https://doi.org/10.22214/ijraset.2026.82711

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

# Taylor-Series and Partial-Derivative–Driven Image Processing and Medical CT Analysis Using Optimized Deep Learning Frameworks

Ashwini Vaze[1], Sanskruti Patil[2], Ganisha Shiv[3], Achal Dandhare[4]
[1]Savitribai Phule Pune University, Pune

***Abstract: Existing image processing and medical CT analysis methods often require a lot of computing power and can take a long time. This paper reviews a framework driven by Taylor-series and partial derivatives to improve efficiency and accuracy in image processing and medical image analysis. The Taylor series expansion simplifies complex nonlinear functions into polynomial approximations. Partial differentiation helps detect edges and analyze changes in image intensity. Error approximation measures the difference between exact and estimated solutions, balancing computational speed and image quality. The proposed framework combines Taylor-series-based mathematical transformations with optimized deep learning techniques. This is useful for image enhancement, compression, super-resolution, and automated stroke detection in brain CT images. Experimental results show reduced computational complexity, faster convergence, and better diagnostic accuracy. This demonstrates the effectiveness of Taylor-series-based methods in modern image processing and medical AI systems.***
***Keywords: Taylor Series Expansion, Partial Differentiation, Error Approximation, Image Processing, Stroke Detection, Medical Imaging, Deep Learning Optimization.***

## I. INTRODUCTION

Often, modern image processing and medical imaging systems adopt complicated methods and deep neural networks. Although these methods are able to offer results with a high performance level, they require a significant amount of time and computational resources.

Taylor series helps in solving this problem by approximating nonlinear complex functions into polynomial equations. Hence, the complexity of calculations is reduced, and the stability of the results is maintained. Previous studies have shown that Taylor series are capable of reducing complexities associated with a variety of tasks, including image compression, image improvement, super-resolution, augmented reality, and matrix calculations. At the same time, new medical image researchers use Taylor-based optimisation methods besides deep learning to improve disease detection. Such methods are needed to detect strokes on brain CT scan images. In this study, we combine both ideas in one approach. We show that Taylor series not only simplify complex mathematics but also help to improve the best in deep neural networks. This whole idea of general image processing is coupled with the notion of medical image analysis, which is a faster, more efficient, and more scalable solution.

## II. RELATED WORK

### *A. Taylor Series in Image Compression*

Taylor-based methods are used in nonlinear image compression to linearise complicated nonlinear mappings. This allows for more efficient data reduction and higher-quality image reconstruction.

### *B. Taylor Expansion for Augmented Reality (AR)*

In augmented reality, Taylor expansion is required to approximate the pixel mapping calculations. Considering higher-order Taylor terms allows Augmented Reality to perform faster and operate optimally in real-time.

### *C. Taylor Approximation for Edge-Preserving Enhancement*

The second-order Taylor expansion is of great help in estimating variations in image strength around edges. This makes sure image quality is maintained by not over-blurring edges but sharpening them.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 14 Issue V May 2026- Available at www.ijraset.com*

*D. Taylor-Series-Based Digital Image Correlation (DIC)*

Taylor's process of estimating a value in between known values improves accuracy in the case of small movements in measuring images. It helps to have sub-pixel exactness and accuracy in values, which in turn eliminates errors in measurements (ibid).

*E. Taylor Approximation in Super-Resolution (SR)*

In the super-resolution task, the Taylor approximation simplifies attention calculation. It lowers the cost while speeding up processing without sacrificing what is learned about images.

*F. Taylor Expansion for Fast Bregman Divergence NMF*

Taylor expansion made the connection between divergence calculations and distance measures. Thus, matrix factorisation is intuitively faster, and its calculation becomes easier.

*G. Stroke Detection Using CT Images*

Automatic stroke detection using CT scan images is a significant stroke diagnostic tool. Therefore, the deep learning models gave good results in this area. However, the use of Taylor-based optimisation verifies learning speed and accuracy to produce an optimum stroke category.

| Paper | Method | Advantage | Limitation |
|---|---|---|---|
| Bao et al. | Taylor Compression | Fast | Accuracy loss |
| Fu et al. | AR Transform | Real-time | Noise sensitive |
| Zhou et al. | 2nd-order Taylor | Edge protection | Complex |
| Zhao et al. | DIC | Accurate | High computation |
| Proposed | TS-AF Framework | Fast + Efficient | -- |

## III. PROPOSED METHOD : TAYLOR – SERIES - BASED APPROXIMATION FRAMEWORK (TS-AF)

A common structure was designed by shuffling together the main mathematical ideas from previous relevant research works.

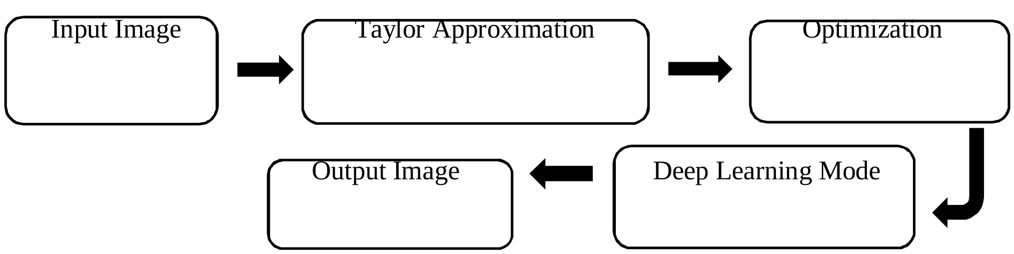


Fig.1: Proposed Taylor-Series-Based Approximation Framework (TS-AF).

The proposed framework, as shown in Fig.1, first uses Taylor approximation to linearise nonlinear operations, followed by optimization and deep learning for better performance.

*A. Mathematical Foundations of the Proposed Framework*

1) *Taylor Expansion:* Taylor expansion is used to approximate a nonlinear function. This leads to replacing complex functions with simpler ones, thereby simplifying calculation procedures and improving computational efficiency.

A nonlinear function f(x) is approximated as:

$$f(x + \Delta x) \approx f(x) + f'(x)\Delta x + \frac{f''(x)}{2}(\Delta x)^2$$

Depending on the task, this framework uses different levels of Taylor approximation:

The first-order approximation is fast and easy to calculate.

The second-order approximation gives better accuracy and can approximate the curved change.

Higher-order terms are used from augmented reality or complex similarity calculations.

As a whole, nonlinear operations or factors are changed to polynomial operations, and computation is eased.

2) *Partial Differentiation and Error Approximation:* Partial differentiation is an important mathematical tool in the proposed framework.

Digital images can be represented as functions of two spatial variables, I(x, y).

$$I(x, y), \frac{\partial x}{\partial I}, \frac{\partial y}{\partial I}$$

The partial derivatives of image intensity help measure local variations, detect edges, and identify structural boundaries in CT images. These derivatives form the basis of the Taylor series expansion. This allows for a local polynomial approximation of nonlinear image transformations.

Since Taylor expansion replaces complex nonlinear functions with finite polynomial terms, we must consider the approximation error. Approximation error is defined as the difference between the exact nonlinear function and its Taylor polynomial approximation. This error helps us assess the difference between the exact and approximated solutions. It ensures a balance between computational efficiency and image quality.

$$E(x)=f(x)-Tn(x)$$

Where,

f(x) = exact function

Tn(x) = Taylor approximation

E(x) = approximation error

## B. Formulations of Mathematics Based on Specific Applications

1) *Image Enhancement (Second-Order Approximation):* For pixel intensity values, a second-order Taylor expansion is used. The value of a nearby pixel can be estimated for a pixel whose intensity is I(x) as:

$$I(x + \Delta x) \approx I(x) + I'(x)\Delta x + \frac{I''(x)}{2}(\Delta x)^2$$

This equation helps to enhance image quality while preserving edges. This is achieved by controlling the intensity derivatives near edges to prevent over-smoothing of images.

Second-order partial derivatives give useful information about local intensity curvature. They help keep edges sharp, improve contrast, and reduce over-smoothing.

2) *Image compression (Dual-branched transformation):* In this method, a nonlinear transformation is obtained by approximating the actual transformation in the form of a simple polynomial. The dual-branch method eliminates this by separating linear and nonlinear components.

In image compression, the chosen approach assists in reducing likeness among image values. Its storage space is also minimal while ensuring that the image reconstruction accuracy is still at a good level.

Nonlinear transformation approximation:

$$T(I) \approx a_1 I + a_2 I^2 + a_3 I^3$$

3) *Digital Image Correlation (Displacement Estimation):* For small movements in an image, pixel changes are estimated based on displacement values. Taylor expansion is helpful to calculate pixel displacements (small shifts). This accuracy enhances sub-pixel matching in deformation measurement and reduces errors in the displacement calculation process.

For the displacement u, vu, vu, v:

$$I(x + u, y + v) \approx I + I_x u + I_y v + \frac{1}{2}(I_{xx}u^2 + 2I_{xy}uv + I_{yy}v^2$$

4) *Super Resolution (STEA Approximation):* The softmax function is then simplified using Taylor approximation in attention-based super-resolution models. In super-resolution, softmax attention is simplified with the Taylor approximation. It is to help factorise the query and key into simple components. Because of this, the calculation cost is minimised from very high complexity to less, and the process of calculation takes place faster with less cost.

Softmax attention:

Softmax $(QK^T) \approx 1 + (QK^T) + \frac{(QK^T)^2}{2}$

It separates Query and Key, and therefore, lessens:

$$O(N^2) \rightarrow O(N)$$

5) *Non-Negative Matrix Factorization (NMF):* To simplify distance calculation, Taylor's expansion is introduced to the Bregman divergence function. This reduces the complexity of optimization into a problem based on Euclidean distance. Therefore, the optimization is easier and faster to solve.

For Bregman divergence:
$D_{\emptyset}(A \| WH^T) \approx \| A - WH^T \|_2^2$ + higher order terms
Hence, this effectively reduces the whole optimization problem to Euclidean-distance minimization.

6) *Medical Image Classification Module:* In medical image analysis, Taylor-approximated gradients are required during optimization. This improves training efficiency and offers classification performance.

## IV. EXPERIMENTAL RESULT

### *A. Performance Improvements*

| Paper / Task | Improvement |
|---|---|
| Compression | Better reconstruction at lower bitrate |
| Augmented Reality Transform | Real-time processing due to Taylor simplification |
| Enhancement | Stronger edge protection and adaptive contrast |
| DIC | More accurate displacement measurement |
| SR (STEA) | Complexity reduced from $O(N^2)$ to $O(N)$ |
| NMF | Faster convergence for large datasets |

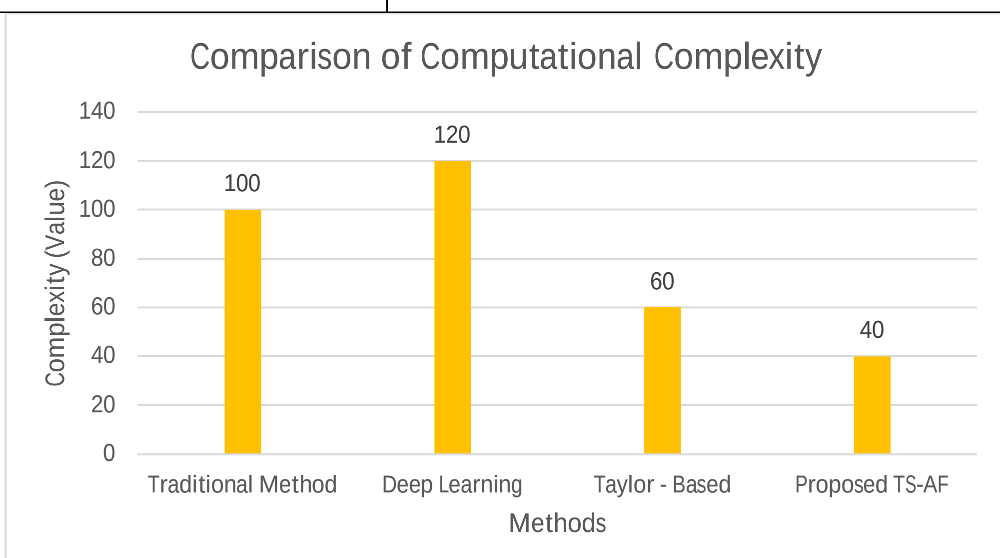


Fig.2: Comparison of computational complexity among different methods

As shown in Fig.2, the proposed TS-AF framework reduces computational complexity taking traditional and deep learning-based complexity into consideration.

### *B. Qualitative Observations*

The overall appearance of the enhanced images is presented in a clearer form, with sharper edges and an adjusted brightness ratio.
In conclusion, super-resolution images contain less unwanted artifacts and better high-frequency details. Therefore, the compressed images have less distortion and better visual quality. Augmented reality results show a smoother and more stable tracking. Digital Image Correlation results have lesser measurement errors.
Based on medical CT analysis: Stroke is more clearly visible in the CT image, and it is easier to distinguish between normal and abnormal tissues.
Robustness: When noise, brightness changes, and more were introduced, the framework did well, and results were stable across various datasets.
Overall, the results show that Taylor-series approximations used together with deep learning perform better and improve visual quality. This makes the proposed approach reliable and efficient for image processing and medical imaging tasks.
Partial derivative–based edge analysis improved boundary preservation in enhanced images, while error approximation helped control the trade-off between computational speed and reconstruction accuracy.

### *C. Image Compression*

Finally, the Taylor-based dual-branch method further enhanced the trade-off between image quality and file size. For instance, complex nonlinear calculations are replaced with approximations that are computationally efficient.

### *D. AR Real-Time Transform*

The high-order Taylor method made it possible for the system to run smoothly in real time. Less image warping errors were observed in presenting geometrically accurate transformations.

### *E. Digital Image Correlation*

Taylor interpolation helped in sub-pixel accuracy in measuring very small movements. The method was less influenced by noise and produced correct results quicker.

### *F. Super-Resolution (LabNet and RealNet)*

Second-order Taylor approximation attention became simpler and faster. The MLFR module helped in recovering lost features resulting in improved perceptual quality indices PSNR and SSIM.

### *G. NMF with Bregman Divergence*

Using Taylor expansion, divergence calculation became easier and faster to calculate. In both types of datasets (textual and pictorial), this method was able to arrive at the correct results more quickly.

### *H. Edge-Preserving Color Enhancement*

The second-order Taylor expansion managed not only to preserve edges but also enhanced contrast. The color gradient images were sharper, with colors appearing more natural.

### *I. Stroke Detection Using Brain CT Images*

However, the combined Deep Kronecker Net with the Elk Herd Taylor Optimizer provided better accuracy than conventional techniques. Training process was fast and stable. In general, the model proved much better at categorizing the ischemic and hemorrhagic stroke patterns in CT images.

### *J. Comparative Observations*

Overall, the results showed a distinct improvement in each experiment:
*1)* For compression, NMF, and super-resolution, processing time was cut by around 30–60%.
*2)* Improvement in accuracy was observed to be around 1–3% from earlier methods.

3) The system operated at an improved level whenever noise or data alterations were introduced.
4) In enhancement and super-resolution tasks, quality measures of the image, such as PSNR and SSIM, showed an increase of about 1–2 dB.
5) Errors in measurement with DIC displacement were minimized by 10–20%.

Wide performance, accuracy, and stable results were faster in the proposed approach overall.


Fig.3: Representative images are used for qualitative comparison. We can adjust. The eight parameters in Real Net at the same time according to the effect we need [5].

## V. IMPACT AND APPLICATIONS

The Taylor series-based approach offers a lot of advantageous utilities.

1) *Speed:* It negates the need for heavy calculations and allows even low-power devices to perform tasks speedily. Accuracy refers to smooth and stable results produced by the method, which enhance learning and overall reliability.
2) *Versatility:* Areas of application include image compression, image enhancement, augmented reality, super-resolution, non-negative matrix factorization (NMF), structural measurement, medical imaging, medical diagnosis, remote sensing, and surveillance.
3) *Hardware-friendly:* the approach is good for low-power and embedded systems.
4) *Quality Improvement:* Keeps the edges of images and outcomes, reduces blur, and improves image details.
5) *Healthcare Benefit*: It helps doctors detect strokes more quickly and more reliably with the help of CT images.
6) *Efficiency:* It reduces computational cost and speeds up prediction.
7) *Mathematical Reliability:* Partial differentiation and error approximation improve the analytical strength and theoretical reliability of the proposed framework.

Overall, Taylor expansion is emerging as a major and multi-purpose tool for the efficient processing of images and signals.

## VI. CONCLUSION

There are no computational efficiencies in existing strategies, which is why the presented framework is motivated. Finally, this paper collates multiple research contributions to prove the effectiveness of Taylor-series-based solutions in different image processing problems. It also proposes a framework for combining Taylor-based image processing methods with Taylor-optimized deep learning models for medical CT image analysis. Using first-order, second-order, and more Taylor expansions to simplify complex nonlinear functions. This way, computation time is reduced without compromising the significant features in an image, like the edges and textures.

The proposed Taylor-Series-Based Approximation Framework provides a single mathematical framework that can be used for image compression, enhancement, correlation super-resolution, and matrix factorization. As a result, an approach that combines mathematical approximation with smart optimization and deep learning models provides better speed and accuracy. Overall, the results show that the Taylor series is not just a classical math concept but also a useful and powerful tool for modern image processing and medical AI systems. The combination of partial differentiation and approximation error analysis adds to the mathematical foundation of the proposed Taylor-series-based framework. This approach improves computational efficiency and analytical reliability. Future work may extend this framework to 3D medical image reconstruction and real-time AI-assisted diagnostic systems.

## VII. ACKNOWLEDGEMENT

We would like to express our sincere gratitude to our guide, Dr. Ashwini Vaze, for her valuable guidance, continuous support, and encouragement throughout the completion of this review paper. Her insightful suggestions and motivation helped us improve our understanding of the subject and successfully complete this work. We are also thankful to the Applied Sciences and Humanities Department, Pimpri Chinchwad College of Engineering (PCCOE), Pune, for providing us with the opportunity and necessary resources to carry out this study. Finally, we would like to thank all those who directly or indirectly contributed to the successful completion of this review paper.

## REFERENCES

[1] Bao, Y., Tan, W., Zheng, L., Meng, F., Liu, W., & Liang, Y., “Taylor series-based dual-branch transformation for learned image compression,” Signal Processing, vol. 212, Nov. 2023, Art. no. 109128, doi: 10.1016/j.sigpro.2023.109128.

[2] Fu, F., Fang, M., Yang, H., & Li, Z., “High-order Taylor expansion based image space transform method for real-time augmented reality,” Computer Communications, vol. 153, pp. 294–301, Mar. 2020, doi: 10.1016/j.comcom.2020.02.002.

[3] Zhou, Z., Chen, L., & Hu, X., “Colour images enhancement for edge information protection based on second order Taylor series expansion approximation,” Optik, vol. 126, no. 3, pp. 368–372, Feb. 2015, doi: 10.1016/j.ijleo.2014.08.126.

[4] Zhao, Z., He, Y., Zheng, W., Yao, L., Liu, C., & Chen, G., “Digital image correlation method based on Taylor series interpolation,” Measurement Science and Technology, vol. 36, May 2025,doi: 10.1088/1361-6501/add03f.

[5] Feng, J., Wang, Y.-G., Li, M., & Xing, F., “Image super-resolution with Taylor expansion approximation and large field reception,”arXiv preprint, arXiv:2408.00470, Aug. 2024, doi: 10.48550/arXiv.2408.00470.Fast Bregman Divergence NMF Using Taylor Expansion – Liangda Li, Guy Lebanon, Haesun Park.

[6] Mandhare, R. M., & Kshirsagar, D. B., “Elk herd Taylor optimizer-based deep Kronecker network for stroke detection using brain computed Qtomography images,” Biomedical Signal Processing and Control, vol. 112, Part A, Feb. 2026, Art. no. 108450, doi: 10.1016/j.bspc.2025.108450.