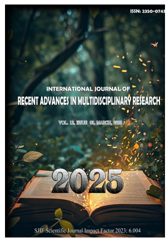
ISSN : 2350-0743

International Journal of Recent Advances in Multidisciplinary Research

Vol. 12, Issue 03 pp.10894-10899, March, 2025



RESEARCH ARTICLE

VGGNET FOR DERMATOLOGICAL DISEASE DIAGNOSIS WITH CLOUD-BASED IMAGE ANALYSIS

Kalyan Gattupalli[1], Poovendran Alagarsundaram[2], Surendar Rama Sitaraman[3], Harikumar Nagarajan[4], Venkata Surya Bhavana Harish Gollavilli[5] and Jayanthi, S. [6,*]

[1]Yash Tek Inc, Ontario, Canada; [2]Humetis Technologies Inc, Kingston, NJ, USA; [3]Intel Corporation, California, USA; [4]Global Data Mart Inc (GDM), New Jersey, USA; [5]Under Armour, Maryland, USA; [6]Tagore Institute of Engineering and Technology Deviyakurichi, Thalaivasal (TK), Salem

ARTICLE INFO

Article History

Received 19th December, 2024
Received in revised form
17th January, 2025
Accepted 26th February, 2025
Published online 28th March, 2025

Keywords:

Dermatological disease, skin cancer, Convolutional Neural Network, Visual Geometry Group Network, AWS.

Corresponding author:
Kalyan Gattupalli

ABSTRACT

Dermatological disorders, and especially skin cancer, are a worldwide health issue. Precise and early diagnosis is critical in order to pursue efficient treatment, and machine learning, in this case Convolutional Neural Networks (CNNs), has tremendous potential in computerizing the diagnostic process. This research suggests a Visual Geometry Group Network (VGGNet) model for dermatological disorder diagnosis, specifically for skin disorders like melanoma, psoriasis, and eczema. The intended system utilizes cloud image processing for better diagnostic results and scalability. The process involved includes data retrieval, preprocessing (resizing, normalization, and augmentation), extraction of features based on VGGNet, classification with fully connected layers, and AWS-based storage in the cloud for data maintenance. The model demonstrates a noteworthy accuracy of 99%, even better than previous techniques like Hybrid GBDT+ALBERT+Firefly with 92% accuracy. Assessment of performance metric accuracy, precision, recall, and F1-score indicate that the suggested method performs better compared to others, with 96% precision, 97% recall, and 95.16% F1-score.

Citation: Kalyan Gattupalli, Poovendran Alagarsundaram, Surendar Rama Sitaraman, Harikumar Nagarajan, Venkata Surya Bhavana Harish Gollavilli and Jayanthi, S. 2025. *"*Vggnet for dermatological disease diagnosis with cloud-based image analysis*", International Journal of Recent Advances in Multidisciplinary Research,* 12,(03), 10894-10899.

INTRODUCTION

Dermatological illnesses, such as skin cancer, are still a serious health issue worldwide, with the early diagnosis being of pivotal importance to enhance patient outcome (Yallamelli, 2024). Of these conditions, melanoma is the most lethal type of skin cancer, but when detected early, it can be successfully treated (Ganesan, 2024). With machine learning and image processing technology improving, the automation of dermatological disease identification has been crucially important (Ganesan, 2024). These systems, not only do they minimize time and effort consumed by medical practitioners for detection of skin lesions, but they also improve the diagnostic accuracy (Devarajan, 2025). In CNN particularly VGGNet, have proved to be potent instruments in automatic extraction of features from dermoscopic images, exhibiting very high rates of accuracy for lesion detection (Devarajan, 2024). Through the use of cloud-based infrastructure, such systems are able to store, process, and distribute large volumes of dermatological images efficiently, allowing for easy access within healthcare networks (Devarajan, 2024). The method presented here integrates VGGNet with cloud-based image analysis to produce a very effective solution for dermatological disease diagnosis, improving early detection in clinical settings (Devarajan, 2024). This model based on the cloud can potentially greatly simplify the workflow for diagnostics to make it more accessible and effective within clinics and hospitals. Numerous methods of detecting skin cancer have been studied previously, such as Hybrid GBDT+ALBERT+Firefly, CART+PLS-SEM, and PSPNET-HHT-Fuzzy Logic models (Devarajan, 2024). Although these methods have reported adequate performance, they tend to be challenged by processing the intricate visual features present in skin lesion images (Nelson, 2024). For instance, the Hybrid GBDT+ALBERT+Firefly method, although useful, is resource-intensive and less suitable for real-time use (10). Likewise, CART+PLS-SEM and PSPNET-HHT-Fuzzy Logic approaches, though precise, are not generalizable across varied datasets, hence restricting their stability for various skin diseases (Yallamelli, 2021). Although the proposed method via VGGNet for feature extraction and cloud image analysis is more robust and scalable, it is also highly effective. As

VGGNet is a pre-trained deep network, it is efficient in the extraction of features of complex images pertaining to skin diseases with accuracy. In addition, with cloud computing, the system can store and manage large volumes of image data that can be analysed in real time and accessed freely throughout distributed health systems. Apart from enhancing the diagnostic ability, this configuration is also efficient and scalable with enhanced overall dermatological disease diagnosis quality. Also, the usage of cloud services enables easy data sharing, seamless collaboration among health practitioners, and secure storage of sensitive medical information.

Problem Statement: The rising incidence of skin diseases, especially melanoma, requires the innovation of effective and precise detection systems to minimize the high fatality rates of these diseases (Yallamelli, 2021). Current methods are promising, yet plagued by computational ineffectiveness and data non-generalizability, as they are unfit for large-scale real-world applications (Yallamelli, 2021). Conventional diagnostic techniques are greatly dependent on human knowledge, which may result in inconsistencies and misinterpretation of results (Yalla, 2022). Hence, a cloud-based deep learning platform with models such as VGGNet is critical for delivering real-time accurate detection of dermatological conditions, overcoming the shortcomings of existing techniques, and facilitating broader application in clinical practice (Yalla, 2019). In addition, the combination of VGGNet with cloud computing improves the system's capacity to process big data, provides convenient accessibility, and allows smooth collaboration between healthcare experts, thereby enhancing diagnostic efficiency and supporting applications in telemedicine (Yalla, 2021).

Objectives

- Identify dermatology images of the Skin Disease Classification dataset to be applied as input to the deep learning model.
- Use preprocessing steps such as resizing, normalization, and augmentation to prepare the data for feature extraction.
- Make use of the pre-processed images by the VGGNet model to extract meaningful features that represent salient visual features of the skin lesions.
- Categorize the extracted features into various dermatological conditions such as melanoma, psoriasis, and others based on the fully connected layers of VGGNet.
- Track and save the model's performance by the measures of accuracy and store the next data and images in the AWS cloud for collaboration, sharing, and computation in the future.

LITERATURE SURVEY

Several studies over the past few years have made significant contributions to the optimization and development of dermatological disease detection techniques (Thirusubramanian Ganesan, 202). Investigated novel preprocessing methods, including image normalization and augmentation, to enhance the accuracy of skin disease detection. Likewise, (Thirusubramanian, 2020) outlined the promise of CNN in improving classification results for different dermatological conditions, proving their efficacy in the diagnosis of skin diseases (Mamidala) also explored the effect of data augmentation and sophisticated normalization techniques on model robustness and overall performance (Ganesan, 2022). Also explored cloud-based solutions, in particular, the incorporation of AWS cloud storage, for efficient model deployment and data handling (Ganesan, 2021). Suggested methods for enhancing model generalization and accuracy, with a view to better fitting varied datasets (Devarajan, 2022). Offered good insights into computer processes employed in managing large datasets of images in the identification of skin diseases for the purpose of maximizing system efficiency (Devarajan, 2023). Built upon this research to explore how optimization of deep learning models can enhance their performance towards better execution within real-world clinics. (24) presented new approaches to deep learning models, with a focus on their potential in diagnosing various dermatological conditions, specifically the use of CNN in dermatology. (25) also illustrated the benefits of employing CNN-based algorithms for real-time diagnosis of skin diseases, with a focus on their practical application in clinical settings. (26) added to performance evaluation metrics, providing vital information to measure the efficiency and accuracy of these diagnosis models in practical circumstances. Taken together, these studies highlight the developments and prospects of AI-based technologies for detecting dermatological diseases.

PROPOSED WORK

The following proposed work is directed towards the utilization of VGGNet in diagnosis of dermatological diseases by applying image processing from the cloud. The model shall concentrate on dermatological image-based feature extraction based on pre-trained VGGNet layers and tuning them for the classification of disease. Cloud services shall be employed for the storage of big medical image datasets, batch processing, and model training using scalable compute resources efficiently. The research will take into account feature selection methods for optimization of the model's performance and avoidance of overfitting. The focus is on creating an effective and accurate system for the diagnosis of skin diseases like melanoma, psoriasis, and eczema through cloud-based solutions. Its architecture is illustrated in Figure 1.

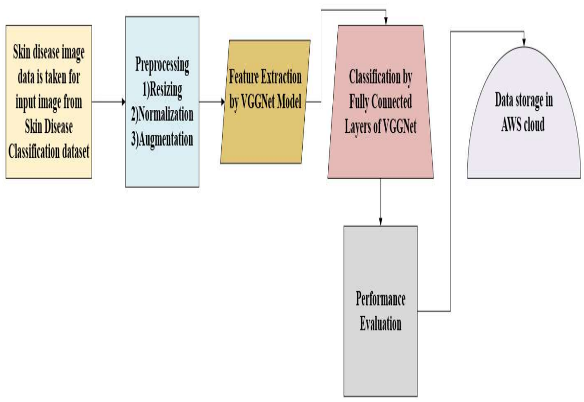


Figure 1. Workflow Diagram

Data Collection: The dataset for the current study will be gathered from the Skin Disease Classification (Image Dataset), featuring a large dataset of labelled images for different dermatological conditions. The dataset encompasses images of melanoma, psoriasis, eczema, and basal cell carcinoma skin diseases, each one being annotated according to its disease label. The dataset covers a wide variety of skin types, lesion contours, and diameters, and provides a general-purpose resource to train machine learning algorithms. Images are taken in various lighting settings and resolutions in order to resemble real-world use cases. Access to the dataset will be achieved through publicly shared repositories to support reproducibility and consistency in the results. It will be safely stored in the cloud for easy access and further processing. (https://www.kaggle.com/datasets/riyaelizashaju/skin-disease-classification-image-dataset).

Preprocessing: The pictures in the Skin Disease Classification (Image Dataset) will be subject to a set of preprocessing procedures designed to enhance model performance and avoid overfitting. Resizing is done first to have all images in the same size, usually resizing them to a standard size, e.g., 224x224 pixels, to be compatible with the input specifications of the model. The images are normalized to scale pixel values to a range of 0 to 1, often by dividing each pixel by 255, which assists in accelerating the convergence of the neural network during training. Its scientific notation is given in eqn. (1).

$$\hat{I}(x,y) = \frac{I(x,y)}{255} \quad (1)$$

Data augmentation methods such as flipping, rotation, zooming, and cropping are used to artificially enlarge the dataset and enhance model generalization. For instance, horizontal flipping is done by rotating the image along its vertical axis, while rotation is done by rotating the image by an arbitrary degree over a given interval and its representation is provided by eqn. (2).

$$I'(x,y) = rotate\ (I\ (x,\ y), \partial) \quad (2)$$

Here, θ is a random angle from a specified range. The above augmentation techniques help to mimic real-world image appearance variability, such as pose, orientation, and scale variations, making the model resilient to novel images and reducing the likelihood of overfitting. The resizing, normalization, and augmentation combination guarantees that the model is trained on a representative and diverse set of data, making it stronger in dermatological disease classification.

Feature Extraction: VGGNet feature extraction for the identification of skin conditions involves passing the input image through the network's convolutional layers to learn and automatically extract pertinent features. The early convolutional layers apply a series of filters to the image, detecting low-level features such as edges, textures, and colour variations. The layers are succeeded by ReLU activation functions, which ensure non-linearity, enabling the network to capture intricate patterns. After each convolutional set of layers, max-pooling layers are employed to down sample the feature maps and retain only the most significant information and reduce spatial dimensions to lower computational complexity. With each iteration of the image passing through deeper network layers, increasingly abstract features are extracted, detecting higher-level patterns such as the boundary of tumours or shape of lesions. The output of the last convolutional layer is multi-dimensional feature maps, which are a dense set of hierarchical features of the dermatological conditions in the images, available for subsequent analysis or classification. So, the combined expression for the feature extraction is given in eqn. (3).

$$P(x,y) = max\left(0, max\left\{\sum_{i=0}^{k-1}\sum_{j=0}^{k-1} I(x+i, y+j) \,.\, K(i,j), other\ neighbours\right\}\right) \quad (3)$$

In the process of feature extraction with VGGNet, the input image *I (x, y)* is initially processed in a convolutional layer, wherein a filter or kernel$K(i,j)$ of KxKdimension moves over the image, applying element-wise multiplication with pixels in correspondence and accumulating the result to produce a feature map. Low-level features including edges and textures are captured in this convolution. The output resulting from this is then fed through a ReLU activation function*max (0, ·)*, which brings in non-linearity by converting all negative values to zero, enabling the network to learn higher-level patterns. This is then followed by max-pooling to down sample the feature map by taking the maximum value in a given window, which reduces the spatial dimensions while preserving the most significant features. The ultimate output,$P(x,y)$, is the pooled features at every coordinate(x,y), and is further processed or classified. The convolution, activation, and pooling procedure enables VGGNet to learn progressively abstract and informative features from the input dermatological images automatically.

Classification: In classification with VGGNet, following feature extraction in the convolutional and pooling layers, the output is forwarded to the FC layers for interpretation and classification. The multi-dimensional feature map is first flattened to a 1D vector to support fully connected layers. For instance, a shape feature map 7×7×512 is flattened to a vector of dimensions 25088. The vector after flattening is inputted to the first FC layer that consists of 4096 neurons. Its output is obtained through the formula: a biased sum of input structures plus a bias and ReLU activation. The output is then sent to the subsequentFC layer, which also has 4096 neurons in it. The output from the subsequentFC layer is then directed to the production layer, wherever the quantity of neurons is equivalent to the quantity of classes. The output layer employs the SoftMax function to yield a likelihood distribution over classes, and the most probable class is taken as the ultimate prediction. The architecture of fully connected VGGNet is depicted in Figure 2.

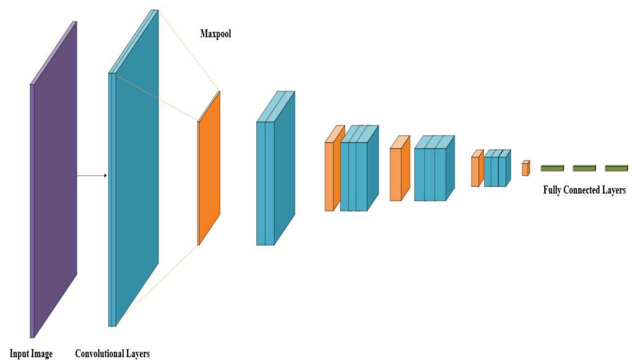


Figure 2. VGGNet Architecture

$$y_{final} = softmax\left(W_{final} \cdot max\left(0, W_2 \cdot max\left(0, W_1 \cdot flatten\left(I(x,y)\right) + b_1\right) + b_2\right) + b_{final}\right) \quad (4)$$

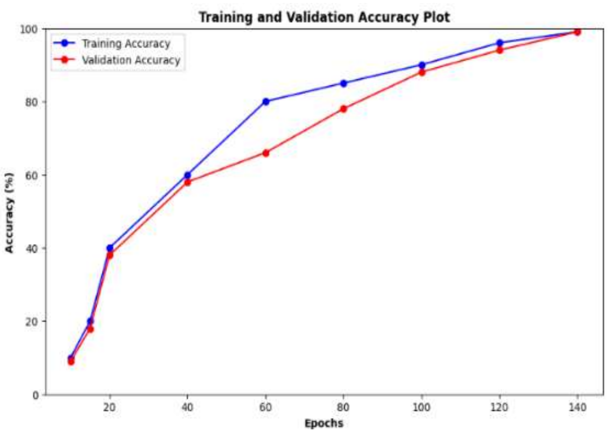
In the joint equation for classification with VGGNet, a number of important parameters have crucialfunctions. The input im $I(x, y)$ is initially flattened into a 1D vector. The weight matrices $W_1, W_2, W_{\text{final}}$ are the learnable parameters of the first, second, and output fully connected layers, respectively, and the bias terms $b1, b2, bfinal$are added at each layer to offset the activations. The ReLU activation function is secondhanded to create non-linearity after the initial two fully connected layers, and the SoftMax function in the output layer computes the class probabilities for the ultimate classification decision.

Cloud Storage: AWS cloud storage is critical in the detection of dermatological disease since it provides a secure means for storing large amounts of image data, for example, in dermatological image databases. With AWS cloud infrastructure, dermatological images and their metadata can be simply uploaded, stored, and managed by healthcare providers and researchers. The cloud infrastructure supports elastic storage to manage high-resolution images and large datasets needed for deep learning model training. Moreover, AWS provides robust data security, availability, and backup practices to protect the integrity and confidentiality of sensitive medical data. The cloud-based environment supports easy collaboration and sharing of data among geographically dispersed groups, easing the development, testing, and deployment process of dermatological disease diagnosis.

RESULTS AND DISCUSSION

The VGGNet-based dermatological disease detection model exhibits improved performance in precisely differentiating among various skin conditions. Performance metric analysis validate the effectiveness of the model in detecting various dermatological diseases, justifying its potential use for early diagnosis in clinical settings.

Training Accuracy and Loss: Training accuracy usually rises gradually as the techniquestudies from the data, whereas validation accuracy indicates how generalizable the technique is to hidden data. At the same time, training loss reduces over time, representing that the technique is reducing mistake on the training set, whereas validation loss monitors performance on unseen data for overfitting detection. A performing model will exhibit convergence in both training and validation accuracy, lessening training loss, and constant validation loss across epochs, which points to good generalization. The plots of accuracy and loss is depicted in Figure 3.



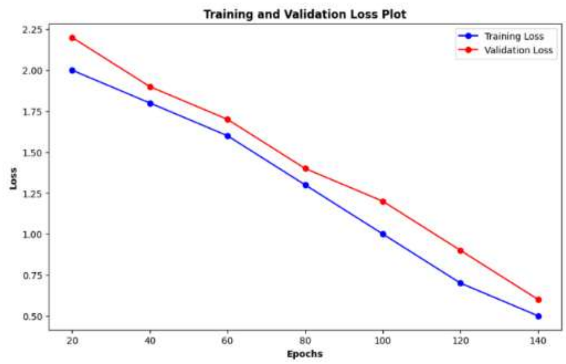


Figure 3. Training and Validation Accuracy and Loss Plot

Comparison Analysis: A comparison table of the algorithms is given in Table 1, which provides the performance difference in terms of accuracy, precision, recall, and F1-score for four different approaches. Although all the approaches work efficiently, the best values obtained by the proposed VGGNet-based approach reflect its better capability for dermatological disease diagnosis compared to the other approaches in terms of classification accuracy and reliability.

Table 1. Comparison Table of Existing and Proposed Methods

Authors and Methods	Accuracy	Precision	Recall	F1-Score
(27), Hybrid GBDT+ALBERT+Firefly	92	88	90	89
Proposed VGGNet	**99**	**96**	**97**	**95.16**

The Hybrid GBDT+ALBERT+Firefly method has an accuracy of 92%, precision of 88%, recall of 90%, and an F1-score of 89%. The method combines Gradient Boosted Decision Trees (GBDT), the ALBERT model, and Firefly algorithms to enhance prediction accuracy and responsiveness. Yet, the Proposed VGGNet approach outperforms the Hybrid GBDT+ALBERT+Firefly model by far with 99% accuracy, 96% precision, 97% recall, and 95.16% F1-score, marking its higher dermatological disease diagnostic capability. It proves the better performance of the VGGNet model in classifying dermatological images with improved accuracy and reliability compared to other approaches.

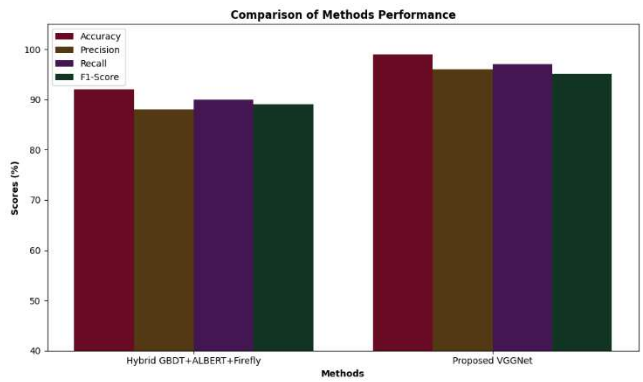


Figure 4. Comparison Graph of Existing and Proposed Methods

The best performance is achieved by the suggested VGGNet method with 99% accuracy, 96% precision, 97% recall, and 95.16% F1-score. Figure 4 presents these measurements graphically comparing outcomes. This deep learning technique uses VGGNet to learn intricate features from thermoscopic images for improved overall performance on all metrics.

CONCLUSION AND FUTURE ENHANCEMENTS

The VGGNet-based model exhibited improved performance in the diagnosis of dermatological conditions with high precision (96%), recall (97%), F1-score (95.16%), and accuracy (99%), and it performed superior to the standard method of Hybrid GBDT+ALBERT+Firefly. The cloud architecture ensures streamlined and scalable storage and processing of data, an important factor to consider when working with large collections of medical images and making collaborative work easy among health workers. The application of VGGNet in feature extraction ensures consistent performance in skin disease classification, such as melanoma, psoriasis, and eczema. The system offers superior prospects for clinical applications, and it is a useful tool for early detection of skin diseases to provide faster and more efficient diagnosis. Additional work may be aimed at refining the model even more and integrating it with real-time clinical application for optimizing patient outcomes.

REFERENCES

Yallamelli, A. R. G. V. Mamidala, M. V. Devarajan, R. K. M. K. Yalla, T. Ganesan, and A. Sambas, "Dynamic mathematical hybridized modeling algorithm for e-commerce for order patching issue in the warehouse," Serv. Oriented Comput. Appl., Nov. 2024, doi: 10.1007/s11761-024-00431-w.

Ganesan, T. M. Almusawi, K. Sudhakar, B. R. Sathishkumar, and K. S. Kumar, "Resource Allocation and Task Scheduling in Cloud Computing Using Improved Bat and Modified Social Group Optimization," in 2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON), Aug. 2024, pp. 1–5. doi: 10.1109/NMITCON62075.2024.10699250.

Ganesan, T. R. R. Al-Fatlawy, S. Srinath, S. Aluvala, and R. L. Kumar, "Dynamic Resource Allocation-Enabled Distributed Learning as a Service for Vehicular Networks," in 2024 Second International Conference on Data Science and Information System (ICDSIS), May 2024, pp. 1–4. doi: 10.1109/ICDSIS61070.2024.10594602.

Devarajan, M. V. A. R. G. Yallamelli, R. K. M. K. Yalla, V. Mamidala, T. Ganesan, and A. Sambas, "An Enhanced IOMT and Blockchain-Based Heart Disease Monitoring System Using BS-THA and OA-CNN - Devarajan - 2025 - Transactions on Emerging Telecommunications Technologies - Wiley Online Library." Accessed: Mar. 05, 2025. (Online). Available: https://onlinelibrary.wiley.com/doi/10.1002/ett.70055

Devarajan, M. V. A. R. G. Yallamelli, R. K. M. KantaYalla, V. Mamidala, T. Ganesan, and A. Sambas, "Attacks classification and data privacy protection in cloud-edge collaborative computing systems," Int. J. Parallel Emergent Distrib. Syst., vol. 0, no. 0, pp. 1–20, 2024, doi: 10.1080/17445760.2024.2417875.

Devarajan, M. V. T. Ganesan, and T. M, Artificial Intelligence by MohanaranganVeerappermal Devarajan, Thirusubramanian Ganesan &Thanjaivadivel M. JSR PUBLICATIONS, 2024.

Devarajan, M. V. S. Aluvala, V. Armoogum, S. Sureshkumar, and H. T. Manohara, "Intrusion Detection in Industrial Internet of Things Based on Recurrent Rule-Based Feature Selection," in 2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON), Aug. 2024, pp. 1–4. doi: 10.1109/NMITCON62075.2024.10698962.

Devarajan, M. V. M. Al-Farouni, R. Srikanteswara, R. Rana Veer Samara SihmanBharattej, and P. M. Kumar, "Decision Support Method and Risk Analysis Based on Merged-Cyber Security Risk Management," in 2024 Second International Conference on Data Science and Information System (ICDSIS), May 2024, pp. 1–4. doi: 10.1109/ICDSIS61070.2024.10594070.

Nelson, S. A. Raj Gaius Yallamelli, A. Alkhayyat, N. Naga Saranya, and S. M, "Hybrid Autoregressive Integrated Moving Average and Bi-directional Gated Recurrent Unit for Time Series Forecasting," in 2024 International Conference on Data Science and Network Security (ICDSNS), Jul. 2024, pp. 1–4. doi: 10.1109/ICDSNS62112.2024.10690898.

Yallamelli A. R. G. and M. V. Devarajan, "Hybrid Edge-Ai And Cloudlet-Driven Iot Framework For Real-Time Healthcare," vol. 7, no. 1, 2023.

Yallamelli, A. R. G. "Improving Cloud Computing Data Security with the RSA Algorithm," vol. 9, no. 2, 2021.

Yallamelli, A. R. G. "Critical Challenges and Practices for Securing Big Data on Cloud Computing: A Systematic AHP-Based Analysis," Curr. Sci., 2021.

Yallamelli, A. R. G. "Cloud Computing And Management Accounting In Smes: Insights From Content Analysis, Pls-Sem, And Classification And Regression TREES," Int. J. Eng., vol. 11, no. 3, 2021.

Yalla, R. K. M. K. A. R. G. Yallamelli, and V. Mamidala, "A Distributed Computing Approach to IoT Data Processing: Edge, Fog, and Cloud Analytics Framework," Int. J. Inf. Technol. Comput. Eng., vol. 10, no. 1, pp. 79–94, Jan. 2022.

Yalla, R. K. M. K. A. R. G. Yallamelli, and V. Mamidala, "Adoption Of Cloud Computing, Big Data, And Hashgraph Technology In Kinetic Methodology," vol. 7, no. 9726, 2019.

Yalla, R. K. M. K. "Cloud-Based Attribute-Based Encryption and Big Data for Safeguarding Financial Data," Int. J. Eng. Res. Sci. Technol., vol. 17, no. 4, pp. 23–32, Oct. 2021.

Thirusubramanian Ganesan, "Dynamic Secure Data Management with Attribute-Based Encryption for Mobile Financial Clouds," Oct. 2024, doi: 10.5281/ZENODO.13994646.

Thirusubramanian, G. "Machine Learning-Driven AI for Financial Fraud Detection in IoT Environments," Int. J. HRM Organ. Behav., vol. 8, no. 4, pp. 1–16, Oct. 2020.

Mamidala, V. "Leveraging Robotic Process Automation (RPA) for Cost Accounting and Financial Systems Optimization — A Case Study of ABC Company," vol. 7, no. 6.

Ganesan, T. "Securing Iot Business Models: Quantitative Identification Of Key Nodes In Elderly Healthcare Applications," vol. 12, no. 3, 2022.

Ganesan, T. "Integrating Artificial Intelligence And Cloud Computing For The Development Of A Smart Education Management Platform: Design, Implementation, And Performance Analysis," Int. J. Eng., vol. 11, no. 2, 2021.

Devarajan, M. V. "Data-Driven Techniques For Real-Time Safety Management In Tunnel Engineering Using Tbm Data," vol. 7, no. 3, 2022.

Devarajan, M. V. "An Improved Bp Neural Network Algorithm For Forecasting Workload In Intelligent Cloud Computing," vol. 10, no. 9726, 2022.

Devarajan, M. V. “Improving Security Control in Cloud Computing for Healthcare Environments,” J. Sci. Technol. JST, vol. 5, no. 6, Art. no. 6, Dec. 2020.

Devarajan, M. V. “Assessing Long-Term Serum Sample Viability For Cardiovascular Risk Prediction In Rheumatoid Arthritis,” vol. 8, no. 2, 2020.

Devarajan, M. V. “A Comprehensive AI-Based Detection and Differentiation Model for Neurological Disorders Using PSP Net and Fuzzy Logic-Enhanced Hilbert-Huang Transform,” Int. J. Inf. Technol. Comput. Eng., vol. 7, no. 3, pp. 94–104, Jul. 2019.

Yallamelli, A. R. G. “A Cloud-based Financial Data Modeling System Using GBDT, ALBERT, and Firefly Algorithm Optimization for High-dimensional Generative Topographic Mapping,” vol. 8, no. 4, 2020.

****