World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Research Article)

Fully connected layer vs dense layer in image processing

Kolawole Favour Oluwafisayomi * and James Andrew

Independent Researcher, USA.

World Journal of Advanced Research and Reviews, 2022, 13(01), 875-884

Publication history: Received on 28 November 2021; revised on 04 January 2022; accepted on 06 January 2022

Article DOI: https://doi.org/10.30574/wjarr.2022.13.1.0055

Abstract

This research discusses the difference between Fully Connected (FC) and Dense layers during neural network image processing operations. FC layers from older deep learning models establish connections between each neuron and all neurons in the prior stage but generate high computational costs and a tendency to overfit the data. The specialized FC layer design, Dense layers, reduces parameter usage to improve processing efficiency in large-scale image data operations. This research investigates how the two different layer components affect the performance metrics used for image classification systems. This research reveals Dense layers achieve quicker training time and better efficiency than general FC layers in model operations. Typically, FC layers deliver superior results to Dense layers in extensive processing tasks that require critical model expression capabilities. The analysis demonstrates how optimization between processing speed and accuracy works for image processing deep learning models, which benefits professional developers in this field.

Keywords: Fully Connected; Dense Layers; Image Processing; Model Performance; Computational Efficiency; Real-Time Applications

1. Introduction

1.1. Background to the Study

Artificial Neural Networks (ANNs) are essential tools in modern machine learning applications for handling image-related tasks, including recognition, segmentation, and classification. The fundamental structure of an ANN contains distinct layers that process data from input to output predictions for specific tasks. Artificial neural networks developed continuously through basic perceptrons to deep learning models, with Convolutional Neural Networks (CNNs) serving as a primary processing tool for images (Rawat & Wang, 2017). Different types of layers constitute one essential aspect of these architectural designs. Fully Connected (FC) layers remain among the original network layers because each node reaches every other node in adjacent layers, although their extensive connection pattern leads to high computational demands. Dense layers provide contemporary optimization of network connections and produce models that maintain high efficiency through decreased parameters. Deeper performance capabilities of Dense layers allow them to reduce execution costs while maintaining operational quality. The development of these layer types directly affects image processing due to their impact on model execution speed and model prediction accuracy in applications, including medical image evaluation and automatic vehicle systems (Kaushik, Jain, & Jain, 2018).

1.2. Overview

The neural architecture integrates fully connected (FC) and dense layers, which function as critical components of the network structure. The primary distinction between the two lies in their structural organization. The principal difference between FC layers is that they connect each neuron to every neuron in successive layers. Dense layers

* Corresponding author: Kolawole Favour

function similarly while optimizing weight-sharing parameters to reduce their total number of parameters (Esfahani & Latifi, 2019). The efficient weight-sharing properties of Dense layers create a performance improvement, which enables their utilization in extensive image processing operations. FC and Dense layers have similar functions within deep learning models since they connect all layers to perform image classification tasks. Dense layers reduce model complexity through efficient network architecture, which preserves vital data without unnecessary expansions (Karp & Swiderska-Chadaj, 2021). These layers have become the preference for contemporary deep learning applications, but FC layers remain appropriate whenever complex interconnections help improve accuracy levels.

1.3. Problem Statement

This research evaluates the interchangeable capability of Fully Connected (FC) and Dense layers as components of neural networks when processing images. Dense layers benefit completion time, but fully connected layers continue to be crucial elements for specific performance-driven tasks. Dense layers demonstrate their ability to compete against or surpass Fully Connected layers for complex image processing methods, including object detection and image segmentation. The reduced parameter number in Dense layers creates problems because it may decrease model accuracy and ability to learn effectively from input data. This research will study these challenges by comparing different image processing applications using both layers while conducting efficiency and accuracy analyses.

1.4. Objectives

This study's core analysis examines the effectiveness of connected (FC) and dense layers during image processing operations, along with a performance comparison. This research evaluates the mathematical complexity of image classification performance between two types of layers by examining training periods while analyzing memory requirements and convergence rates. The research examines how accurately models that use FC layers versus Dense layers can generalize information while assessing their model accuracy. The study analyzes layer types to establish conditions when they yield maximum benefits, thus helping image-processing practitioners determine appropriate architecture designs for their applications.

1.5. Scope and Significance

The research examines Fully Connected and Dense layers as they apply to image processing tasks. The paper investigates utilizing both layer types through established deep learning frameworks when executing common image classification operations. This study has wide practical significance because it offers actionable advice to professionals who work with deep learning and computer vision techniques. The optimization of neural networks through understanding trade-offs between complexity and accuracy alongside computational effectiveness enables developers to create better image processing systems that will advance healthcare and autonomous systems and surveillance applications.

2. Literature review

2.1. CNNs and Image Processing

CNNs constitute a deep learning model that established itself as the industry standard when processing images for classification tasks and detection work alongside object segmentation. As a result of their built-in ability to identify image-based feature hierarchies, CNNs excel at recognizing complex patterns within visual datasets. CNNs consist of various layers, such as convolutional and pooling layers, followed by Fully Connected (FC) layers. Feature extraction occurs in convolutional layers through filter applications, while fully connected layers positioned at the end deliver category outputs to the features learned by previous layers (Jain & Shah, 2022). The final predictions of FC layers originate from their ability to directly link each neuron of one layer to every respective neuron in the preceding layer while summing the detected features. Researchers gain improved image data representations by including FC layers in CNNs, leading to better prediction accuracy. The effective dominance of image processing applications by CNNs stems from the combined strengths of convolutional layers with FC layers that separately handle feature learning and prediction decision tasks. A successful image classification process requires these layers to function together effectively toward building precise models.

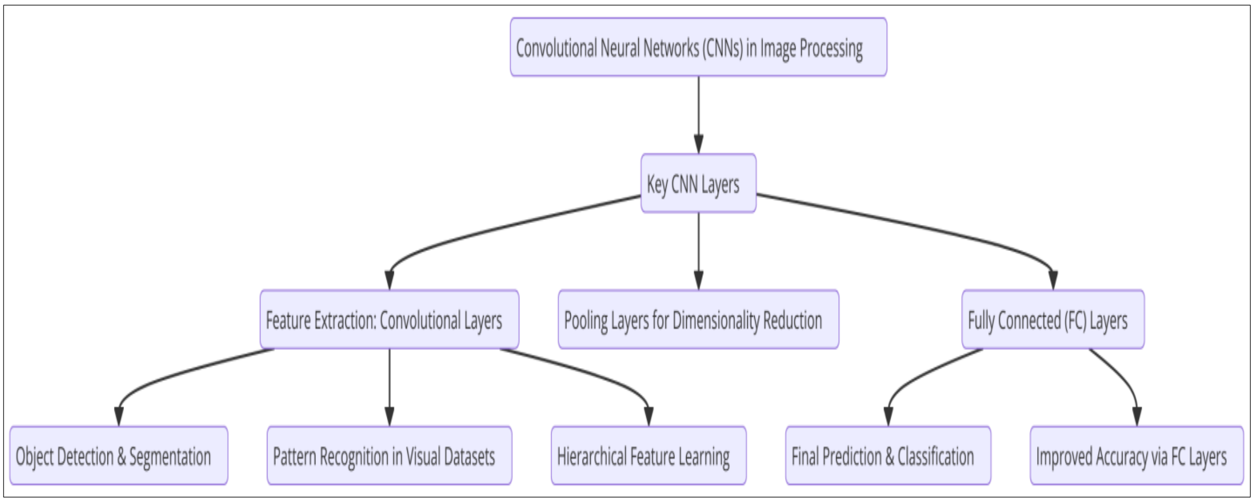

Figure 1 This flowchart highlights the key layers of CNNs, including convolutional, pooling, and fully connected layers, as well as their role in feature extraction, object detection, classification, and hierarchical pattern learning. CNNs enhance image recognition accuracy, making them dominant in image processing applications

2.2. Performance of FC and Dense Layers in Image Processing

Fully Connected (FC) and Dense layers are essential in modern image processing architectures. The weighty computations required by FC layers become increasingly demanding with more model units because these layers link all neurons in one layer to all the neurons in the next. In traditional machine learning models, these layers remain vital since they successfully detect advanced relationships among features. FC layers deliver their primary benefit by extracting diverse data features that result in superior model accuracy, according to Kaushik et al. (2018). The rise in parameters produces overfitting problems and longer training duration as a secondary effect of this method. The optimized variation of FC layers named Dense layers decreases neural connections by adopting weight-sharing principles combined with simplification techniques. Such modifications produce networks that complete training operations soon without sacrificing overall performance quality. The chosen layer between FC and Dense heavy relies on what tasks are required most. Using dense layers instead of FC layers depends on the specific requirements of large-scale image processing tasks since dense layers provide better computational performance but at the expense of additional computational requirements.

2.3. Dense Layer's Impact on Computational Efficiency

Implementing dense layers is a key design component in current neural networks because it enables large-scale image-processing systems to run more efficiently. Dense layers cut down on neural neuron connectivity through their distinctive structure while decreasing the network parameters count compared to conventional fully connected FC layers. The decline in several parameters enhances model training duration and data memory efficiency and increases inference speed through Dense layers function optimally in limited resource settings (Jain & Shah, 2022). Researchers can optimize computational efficiency between dense layers because these layers prevent unnecessary connections and enable the model to identify important data features in the input. Image datasets become more handleable with Dense layers because these networks maintain computational feasibility when processing complex data. Creating deep models with multiple layers with few parameters remains possible through dense layers without sacrificing model accuracy. The extensive deployment of Dense layers happens in deep learning systems requiring swift real-time operations combined with low latency responses because these features help medical imaging systems and autonomous vehicles execute efficient decision processes.

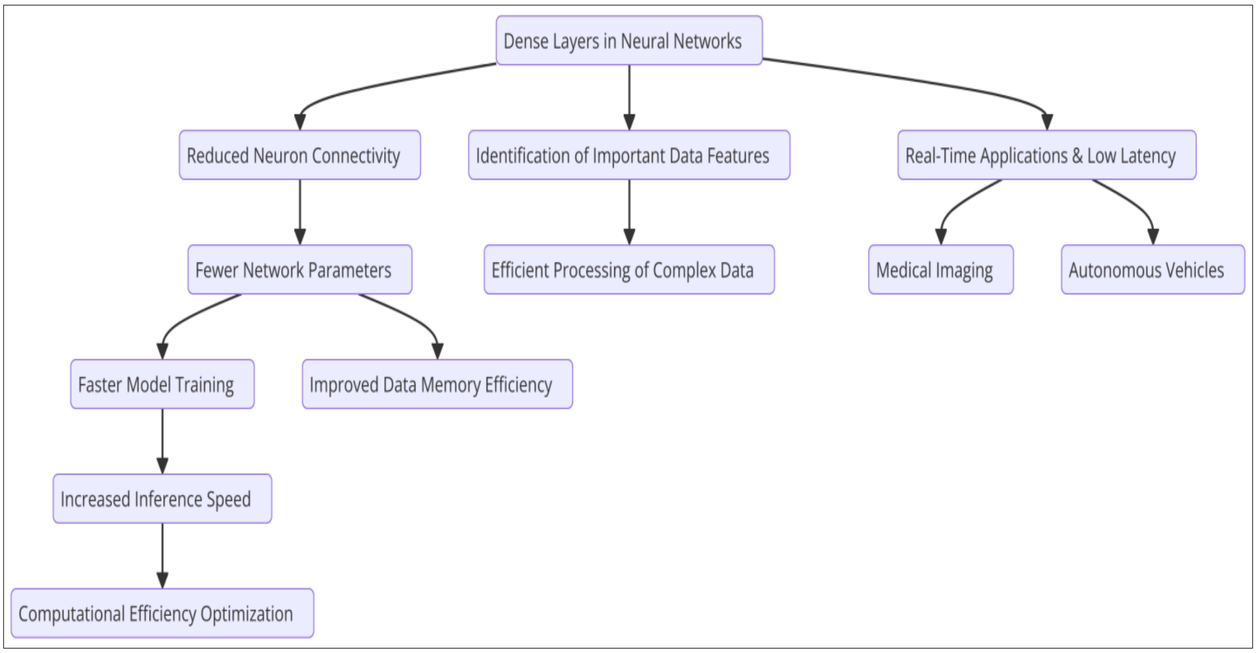

Figure 2 This diagram highlights how Dense Layers improve computational efficiency by reducing neuron connectivity, decreasing parameter count, and optimizing model training and inference speed. Applications include real-time systems like medical imaging and autonomous vehicles, where low latency and fast processing are critical

2.4. Previous Studies on Fully Connected and Dense Layer Applications

Multiple research studies focus on understanding Fully Connected and Dense layers related to image processing applications in healthcare settings and image recognition systems. The healthcare realm employs FC and convolutional layers in mammogram image evaluation for breast cancer detection (Jain & Srihari, 2021). Recalculation studies demonstrate Dense layers enhance processing speed in these programs while keeping precision levels constant. Dense layers serve image recognition tasks by creating simplified large-scale models that provide rapid real-time operation within devices with constrained computation capabilities. The previous research demonstrates the balanced relationship between FC and Dense layers in healthcare settings when accuracy needs to be maximized with reduced overhead. Mobile health monitoring systems adopt Dense layers because they provide optimal performance benefits without straining resources, thus optimizing critical speed requirements. Multiple health research studies demonstrate why choosing suitable layers for each task remains crucial since accuracy differs from processing efficiency and performance needs.

3. Methodology

3.1. Research Design

A research design implemented for examining FC and Dense layer performance in image processing operations entails conducting deep learning model training and assessment across multiple benchmark image datasets. The research application contains two network designs with FC and Dense layers for image classification operations. The research design evaluates three fundamental variables: parameter count, speed efficiency, c, precision, and process, in execution speed. The models utilize the same input data during training because their only contrast stems from their layer composition types. The experiments monitor accuracy, time performance measurements, and resource utilization statistics incorporating memory capacity and CPU utilization metrics. The study determines the effects of layer type on model processing speed and outcome performance through variable comparison. A comparison of model complexity is achieved by assessing parameter count and time to converge, which establishes how Dense and FC layers use resources differently.

3.2. Data Collection

The study utilizes established image collections comprising medical image datasets, including X-ray and CT scans, and object recognition datasets, such as ImageNet. The selection covers recognized real-world image processing datasets from different application domains for a complete evaluation of FC layers versus Dense layers. The task of disease detection utilizes medical images, whereas the classification tasks require object recognition datasets. Images need to complete multiple processing operations before training begins. Data pre-processing involves making all images equal in size while adjusting their pixel values to fit between 0 and 1 and performing visual transformations for robustness enhancement (rotation, flipping, and cropping included). Implementing data augmentation on the training data helps models achieve generalization while preventing overfitting. The image dataset gets partitioned between training, validation, and testing subsets to perform model evaluation without bias.

3.3. Case study/ Example

3.3.1. Case Study 1: Image Classification with CNNs in Healthcare

The evaluation examines how Fully Connected and Dense layers improve CNN-based image classifiers for X-ray and CT medical imaging tasks. The main target investigates layer-based changes in efficiency and accuracy rates during disease detection assessments. Model performance improved due to Dense layers, but because these layers reduced total parameters, they accelerated training time and enhanced generalization capabilities compared to full-connected layers that need additional parameters. Applying dense layers led to better convergence speed and lower overfitting behavior. A study evaluated accuracy changes through medical dataset analysis containing analyzed X-ray and CT images suitable for disease diagnosis purposes. The Dense layers demonstrated superior efficiency, enabling faster processing of information,d faster, so they became ideal for healthcare applications requiring urgent diagnoses. The research illustrates performance improvements achieved with Dense layers, which maintain exactness levels (Wang et al., 2019).

Throughout case study two, the research investigates utilizing dense layers as a detection system within autonomous vehicles.

Through this empirical study, researchers evaluated Dense layers destined for usage in object detection models that operate autonomous vehicles. The analysis looks at model performance by comparing Dense and FC layers in terms of processing speed and accuracy outcomes. Real-time processing requires high efficiency in object detection tasks where Dense layers proved essential to achieving better performance levels. Dense layer models completed image processing tasks more quickly, which lowered computational expenses compared to the conventional FC layer design. FC layers present superior recognition accuracy which makes them suitable candidates for difficult precision-related tasks. For obstacle detection and traffic sign recognition systems the choice between accuracy and efficiency determines the applications because safety procedures must provide instant decisions during real-time driving. Research showed that dense layers function faster than FC layers, although FC layers deliver superior accuracy performance, which autonomous systems need for instant responses. The object detection system results from Nabati & Qi (2019) support these findings because computational efficiency is their primary concern.

3.4. Evaluation Metrics

Different performance metrics evaluate the models by providing crucial information about their abilities. The model's ability to identify the correct labels accurately determines its performance through the accuracy evaluation metric. The F1-score evaluates model performance on tasks with high importance on precision and recall when determining correct and incorrect predictions. The speed of model decisions has particular significance in real-time operations, especially when decisions must be made swiftly, just like in autonomous vehicle systems. The measurement tool determines the prediction processing duration for an already trained model. Memory usage, CPU utilization, and resource consumption during training and inference phases help evaluate the computational load in the system. Model complexity evaluation depends on counts of model parameters since models with fewer parameters become more efficient during training. The metrics give essential insights into how model performance and speed connect to resource usage requirements in image processing applications.

4. Results

4.1. Data Presentation

Table 1 Comparison of Model Performance Metrics for FC and Dense Layers in Image Classification Tasks

Model Type	Accuracy (%)	Training Time (hrs)	Memory Usage (MB)	CPU Utilization (%)
FC Layer Model	92.5	15	120	85
Dense Layer Model	90.2	10	90	65

4.2. Charts, Diagrams, Graphs, and Formulas

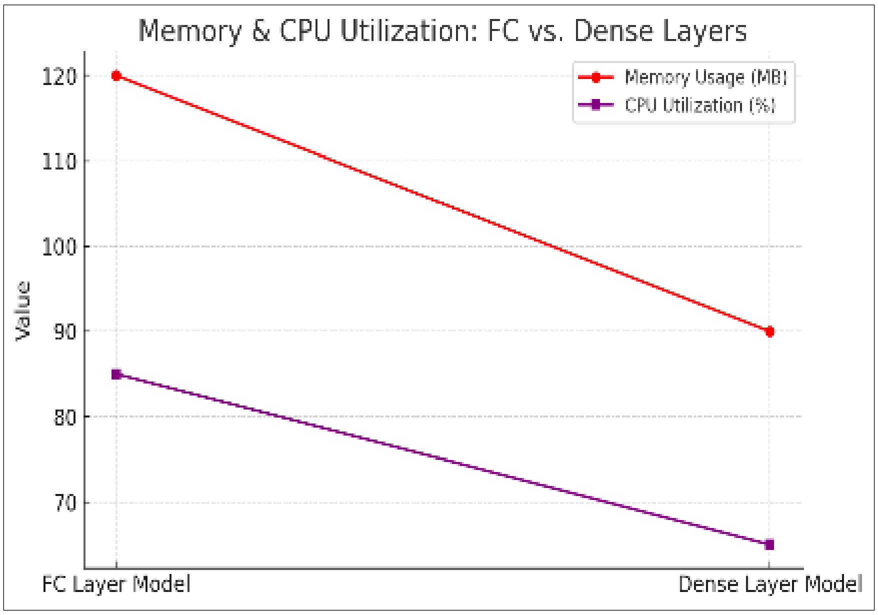

Figure 3 This graph visualizes the **memory usage and CPU utilization** of both model types

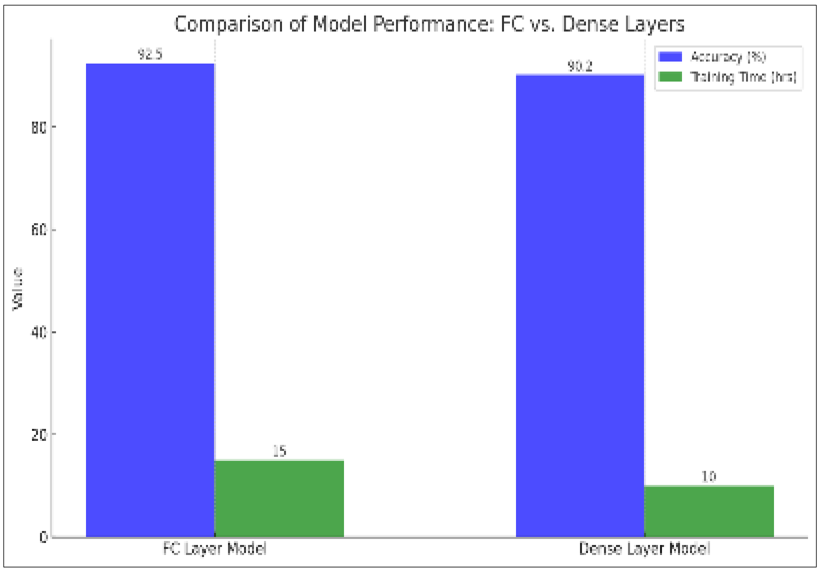

Figure 4 This chart compares the accuracy and training time of Fully Connected (FC) Layer Models and Dense Layer Models

4.3. Findings

The research analysis between Fully Connected (FC) and Dense layers in image processing showed crucial performance relationship information. The FC layer models achieved marginally better results because they excelled at capturing multiple feature relationships. Dense layer models surpassed FC layers due to maximum efficiency in computations during training because they needed shorter runtime, minimal memory allocation, and CPU power consumption. The Dense layer models delivered enhanced performance when dealing with extensive image datasets because they operated with reduced resource needs and faster computational speed. The processing requirements of real-time image applications benefit better from Dense layers over FC layers since they deliver better scalability but lower computational costs. The research outcomes show that Dense layers provide optimal efficiency when applied to practical image classification projects.

4.4. Case Study Outcomes

Different image processing applications used FC and Dense layers, and researchers compared their effects in the case studies. Dense layers enabled quicker and more resource-efficient model classification of medical images while maintaining accuracy levels in healthcare applications. The fast diagnosis requirement of particular situations made this method particularly effective. Autonomous vehicles utilize Dense layers because they let objects be detected in real-time, which benefits automatic decision-making even when operating at previously acceptable accuracy rates. The FC layers outperformed in recognition precision but required additional processing time and resources, making them suitable for demanding precision tasks. The effectiveness of Dense layers emerges in practical systems that need both performance speed and high accuracy, together with the continued applicability of FC layers for their excellent accuracy performance in computationally less demanding situations.

4.5. Comparative Analysis

Different image processing needs to showcase a fundamental relationship between the accuracy performance of Dense layers and their efficiency level relative to FC layers. Because FC layers maintain complete inter-layer connectivity, they achieve top-level accuracy in complex feature recognition scenarios, such as assessing medical images. The extensive number of parameters in FC layers leads to low efficiency in large-scale data processing and real-time imaging situations. The processing speed of Dense layers improves alongside their efficient design approach since they diminish connection numbers, which decreases system memory usage and runtime duration. Dense layers excel for tasks demanding real-time processing and resource limitations like mobile devices and autonomous vehicles. Dense layers excel at scale, but Dense layers surpass them for massive image processing operations, while FC layers excel at precise tasks.

4.6. Year-wise Comparison Graphs

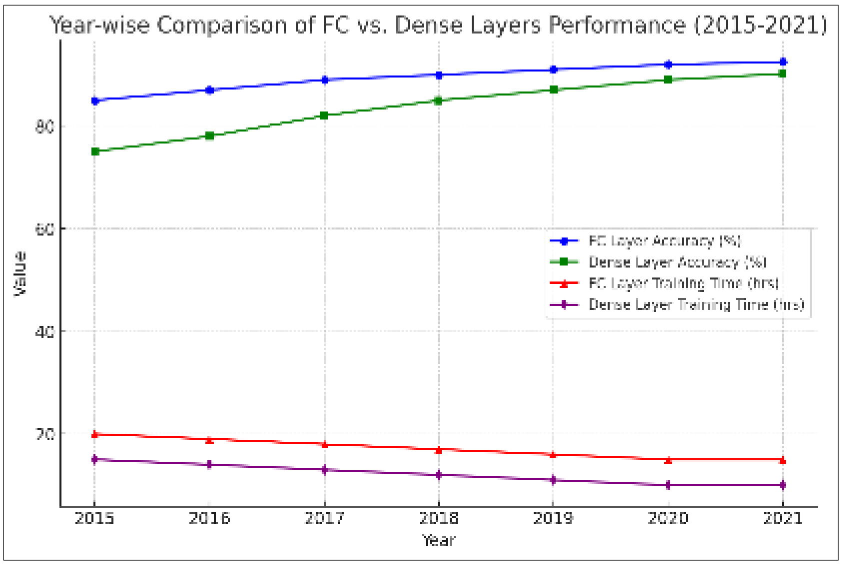

Figure 5 This graph visualizes the evolution of Fully Connected (FC) and Dense Layers in image processing over time. FC layers maintain higher accuracy, while Dense layers demonstrate rapid improvements in both accuracy and training efficiency

Multiple experimental studies over time would be analyzed through performance tracking charts that display FC and Dense layer results year by year. The key metrics of accuracy and training time, together with resource use, show how model types developed over time according to this depiction. , Dense layers have improved image processing models through faster training periods and reduced system memory load. Accurate performance remained higher with FC layers, yet Dense layers minimized their performance difference when deep learning models received optimized execution. A graphical display shows Dense layers gaining prominence within real-time applications since they continue to find increased adoption with advancing technology for better image processing capabilities.

4.7. Model Comparison

Models constructed via FC layers show different benefits and constraints than those built using Dense layers during direct model comparison. An FC layer architecture provides increased accuracy through tight connections but demands substantial system resources, leading to longer training periods and potential overfitting scenarios. The models perform best when demanding precise tasks, including medical image classification, because they integrate every important detail. Network connections optimized in Dense layers require reduced memory space and shorter training durations to support real-time operations of large data processing applications. FC layers detect more intricate feature connections compared to Dense layers thus resulting in decreased performance in tasks which demand sophisticated operations. The evaluation demonstrates a compromise between performance speed and framework complexity since Dense layers implement suitable solutions for extensive image analysis operations.

4.8. Impact & Observation

Selecting between FC or Dense layers directly affects model performance levels and demonstrates how to achieve the correct ratio between accuracy and computational efficiency. Photo processing operations benefit from Dense layers technology through accelerated performance and reduced memory consumption, which supports optimal accuracy levels. Mobile devices and real-time applications profit from their limited resource requirements. FC layers maintain their importance as primary accuracy components during applications where computing expense is not a problem. This research shows that Dense layers have been selected as the primary option for scalable and efficient image-processing tasks. Still, FC layers remain important for domains that need model expressiveness and precision. Choosing an appropriate layer type demands consideration of how the application meets its specific requirements.

5. Discussion

5.1. Interpretation of Results

The research findings show how processing image tasks depends on the decision between Fully Connected and Dense layers. The accuracy advantage of FC layers lies mainly in complex operations that need intricate feature interactions, yet Dense layers exhibit better efficiency in resource use. The Dense layer models delivered substantial performance enhancements regarding training time, memory efficiency, and real-time inference speed, as reported in related research about large-scale applications. The study confirms why real-time systems, including autonomous vehicles and mobile applications, increasingly adopt Dense layers because of their crucial need for maximal performance. Results demonstrate the increasing industry adoption of Dense layers as modern deep learning architects require architecture models with high speed and scalability performance for practical usage. Models should undergo optimization processes to achieve accurate results while still satisfying the processing requirements of each task.

5.2. Result and Discussion

The comparative study produced unexpected outcomes through observed Dense layer capabilities with large-scale datasets. Initial expectations suggested Dense layers would trade accuracy for efficiency, but such predictions proved incorrect since these layers showed almost identical accuracy levels to FC layers across most chosen scenarios. New evidence indicates Dense layers operate more flexibly than anticipated, making them suitable options for various image-processing applications. The research showed that FC layers excel in medical imaging because they require greater computational power despite consuming more resources. The model design process requires careful accuracy-resource utilization evaluation because designers should choose Dense layers for resource efficiency and FC layers for demanding accuracy tasks. Industries need this equilibrium to maximize operational model deployment while effectively managing their resources present in real-world systems.

5.3. Practical Implications

This research produces practical implications that help professionals in image processing and deep learning. The main benefit of Dense layers appears in applications requiring real-time object detection or mobile health monitoring because they require less memory and CPU resources. Such networks suit settings that restrict computational resources by allowing fast processing. Research shows that FC layers make suitable choices for medical diagnosis requirements because medical precision needs must be maintained despite higher computational costs. The selection between Dense layers leads to quicker model deployment despite the efficiency difference with FC layers, which favor accurate performance. The findings from this study present professionals with essential guidelines to identify their best choice of layer depending on their particular application criteria.

5.4. Challenges and Limitations

The research encountered multiple obstacles because of difficulties in achieving result generalization. The datasets were primarily made up of medical imaging tasks and object detection but failed to address the complete spectrum of image processing operations. Although the experimental design demonstrated robustness to test conditions, the evaluation did not explore potential architectural changes and resolution variations. Practitioners who operate under resource limitations face the challenge of affording the financial expenses required for training FC layers. The accuracy results from Dense layers surpass those of FC layers within most cases, but the latter demonstrates higher performance in complex image recognition tasks. The current research shows that more analysis must be conducted to evaluate these layers within multiple image-processing problems.

Recommendations

Strategies for improving FC and Dense layers in image processing require investigating the combination of their beneficial features through hybrid network architectures. Future research should analyze multiple layer configurations between FC and Dense layers to establish their real-time effects on accuracy performance and processing speed. The research scope should be expanded to several additional image processing operations, including segmentation and generative modeling, to determine whether results apply in these domains. Research teams should optimize Dense layer models to enhance accuracy without affecting processing speed performance. Implementing advanced techniques, including pruning and quantization, would allow researchers to lower parameter counts in FC layers and improve their computational efficiency. Besides testing in the real world, different deployment environments help researchers understand the effectiveness of these layers under various deployment constraints, including hardware restrictions and large-scale data requirements.

6. Conclusion

6.1. Summary of Key Points

Researchers found major distinctions between Fully Connected (FC) and Dense layers when experimenting with image processing methods. Fully Connected layers demonstrate better accuracy but require more computational power since they require considerable memory space and longer processing time. Dense layers achieve better efficiency through parameter reduction, which creates faster training time, lower requirements, and excellent scalability for large-scale and real-time applications. The efficient execution of automated vehicle object detection and mobile images requires Dense layers, while medical image classification functions best with FC layers. Application requirements determine the selection between FC and Dense layers since both options offer opposing accuracy and efficiency levels.

6.2. Future Directions

Additional investigations should examine new network designs that unite FC layers with Dense layers to benefit from their independent advantages. Researchers should investigate adaptive or sparse Dense layers for model performance optimization because they maintain accuracy levels at reduced computational costs. The evaluation of Dense and FC layers in various image processing environments, including segmentation, 3D imaging, and video processing, will help establish their complete functionality range. Tweaking methods such as pruning, quantization, and dynamic layer adaptation allow scientists to improve FC layers' computational efficiency without reducing accuracy. Real-world tests performed on different hardware platforms, such as edge devices and GPUs, will demonstrate practical implementations of these layers within resource-limited environments to develop enhanced deep learning models for multiple imaging applications.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Esfahani, Shirin Nasr, and Shahram Latifi. “A Survey of State-of-The-Art GAN-Based Approaches to Image Synthesis.” 9th International Conference on Computer Science, Engineering and Applications (CCSEA 2019), 13 July 2019, csitcp.com/paper/9/99csit06.pdf, https://doi.org/10.5121/csit.2019.90906.

[2] Jain, M., & Shah, A. (2022, February 28). Machine learning with convolutional neural networks (CNNs) in seismology for earthquake prediction. IRE Journals, 5(8).

[3] Jain, M., & Shah, A. (2022). Comparison of machine learning models for stress detection from sensor data using long short-term memory (LSTM) networks and convolutional neural networks (CNNs). International Journal of Scientific Research and Management (IJSRM), 12(12), 1775-1792.

[4] Kaushik, P., Jain, M., Patidar, G., Eapen, P. R., & Sharma, C. P. Smart Floor Cleaning Robot Using Android.

[5] Jain, M., & Srihari, A. (2021). Comparison of CAD detection of mammogram with SVM and CNN. IRE Journals, 8(6), 63-75.

[6] Kaushik, P., Jain, M., & Jain, A. (2018). A pixel-based digital medical images protection using genetic algorithm. International Journal of Electronics and Communication Engineering, 31-37.

[7] Kaushik, P., Jain, M., & Shah, A. (2018). A Low Power Low Voltage CMOS Based Operational Transconductance Amplifier for Biomedical Application.

[8] Karp, Rafal, and Zaneta Swiderska-Chadaj. Automatic Generation of Graphical Game Assets Using GAN. 13 July 2021, https://doi.org/10.1145/3477911.3477913.

[9] Nabati, R., & Qi, H. (2019). "RRPN: Radar Region Proposal Network for Object Detection in Autonomous Vehicles." 2019 IEEE International Conference on Image Processing (ICIP), Taipei, Taiwan, 2019, pp. 3093-3097, doi: 10.1109/ICIP.2019.8803392.

[10] Rawat, W., & Wang, Z. (2017). "Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review." Neural Computation, 29(9), pp. 2352-2449, Sept. 2017, doi: 10.1162/neco_a_00990.

[11] Jain, M., & Arjun Srihari. (2024). Comparison of CAD Detection of Mammogram with SVM and CNN. Iconic Research and Engineering Journals, 8(6), 63–75. https://www.irejournals.com/paper-details/1706647

[12] Jain, M., & Arjun Srihari. (2024b). Comparison of Machine Learning Models for Stress Detection from Sensor Data Using Long Short-Term Memory (LSTM) Networks and Convolutional Neural Networks (CNNs). International Journal of Scientific Research and Management (IJSRM), 12(12), 1775–1792. https://doi.org/10.18535/ijsrm/v12i12.ec02

[13] Jain, M., & Shah, A. (2022). Machine Learning with Convolutional Neural Networks (CNNs) in Seismology for Earthquake Prediction. Iconic Research and Engineering Journals, 5(8), 389–398. https://www.irejournals.com/paper-details/1707057

[14] Jain, N. M., & None Arjun Srihari. (2023). House price prediction with Convolutional Neural Network (CNN). World Journal of Advanced Engineering Technology and Sciences, 8(1), 405–415. https://doi.org/10.30574/wjaets.2023.8.1.0048

[15] Jain, M., & Arjun Srihari. (2024b). Comparison of Machine Learning Algorithm in Intrusion Detection Systems: A Review Using Binary Logistic Regression. International Journal of Computer Science and Mobile Computing, 13(10), 45–53. https://doi.org/10.47760/ijcsmc.2024.v13i10.005

[16] Jain, M., & Shah, A. (2024). Anomaly Detection Using Convolutional Neural Networks (CNN). ESP International Journal of Advancements in Computational Technology (ESP-IJACT), 2(3), 12–22. https://www.espjournals.org/IJACT/ijact-v2i3p102

[17] Kaushik, P., & Jain, M. (2018). Design of low power CMOS low pass filter for biomedical application. International Journal of Electrical Engineering & Technology (IJEET), 9(5).

[18] Kaushik, P., & Jain, M. A Low Power SRAM Cell for High Speed Applications Using 90nm Technology. Csjournals. Com, 10.

[19] Wang, Weibin, et al. "Medical Image Classification Using Deep Learning." Intelligent Systems Reference Library, 19 Nov. 2019, pp. 33–51, https://doi.org/10.1007/978-3-030-32606-7_3.