A Novel CNN-Based BEOL Contour Modeling Solution for Parasitic R/C Extraction

Orion C. H. Yu*, Jim Liang, Gary Lee, C. T. Lee, W. B. Luo, K. Y. Su, K. W. Su, K. L. Cheng, and C. K. Lin
Taiwan Semiconductor Manufacturing Company
Hsinchu, Taiwan
*Email: chyuzk@tsmc.com

***Abstract*—In this article, we propose a machine-learning (ML) based wafer contour approach for parasitic R/C modeling, leveraging a convolutional neural network (CNN) architecture. We demonstrate that our NN critical dimension (CD) model outperforms traditional rule-based approaches in predicting metal contours. With this capability, our NN RC-model exhibits excellent accuracy in predicting parasitic R/C. Furthermore, our NN RC-model is more efficient than the conventional 3D field solver tools. This demonstration manifests the possibility of an electrical-aware pattern optimization, enabling the co-optimization from layout design to final electrical performance through the CNN-based CD/RC algorithm.**

Keywords—machine-learning, neural network, critical dimension, BEOL modeling, parasitic R/C extraction

I. Introduction

The impact of parasitic R/C has become increasingly critical for circuit performance in advanced nodes [1-5]. Traditional R/C extraction methods include the 3D field solver and the 2.5D rule-based approximation. The 3D field solver addresses Maxwell's Equations to determine parasitic C among metal polygons. While it offers the highest accuracy, it is extremely slow and memory-intensive, making it unrealistic for large-scale circuits. To address this limitation, the 2.5D rule-based approach was developed. Compared to the 3D field solver, the 2.5D ruled-based method enables significantly faster extraction with reasonable accuracy of a full chip. This is achieved through pre-characterization and patten matching techniques [4-5]. However, the 2.5D approach still faces several challenges, such as limited pattern coverage that results in accuracy loss in complex environments, prolonged lead time due to the growing numbers of pre-characterized capacitance in the 3D solver as technology evolved, and the increasing accuracy demands for advanced nodes [4-6].

Another factor that may affect the accuracy of parasitic R/C extraction from original design is the adjustment of lithography pattern on wafer for better process window. Industries have traditionally modeled this with overly simplified formulas, leading to inaccurate metal CD (and thus extracted R/C values). Therefore, how to accurately predict metal CD is crucial in modern IC design. Convolutional neural networks (CNNs) have been successfully demonstrated to excel in image processing [7-8], making them a promising approach to tackle the aforementioned challenges. In this study, we introduce a CNN-based model that accurately predicts the physical wafer CD and parasitic R/C utilizing simulated wafer images as input.

This paper is organized as follows. Section II describes the NN methodology used in this paper. In Section III, we examine the accuracy and efficiency of NN-predicted contour/R/C models, comparing the results with commercial EDA 3D and 2.5D RC extraction tools. Finally, the conclusions are drawn in Section IV.

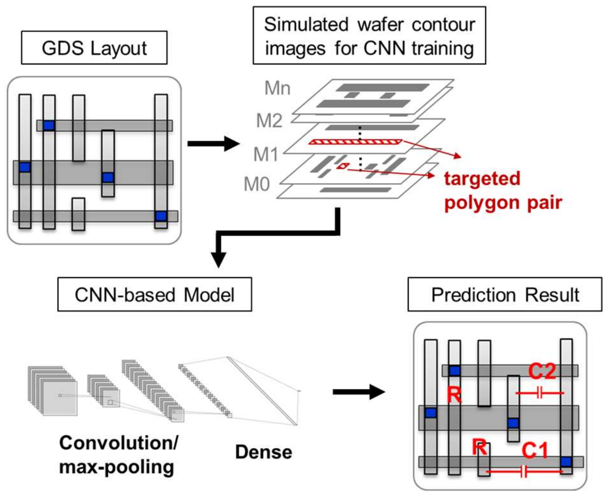

Fig. 1. The flow-chart of our CNN-based modeling methodology. The input data is pre-processed from drawn GDS layouts to simulated wafer contour images for CNN training.

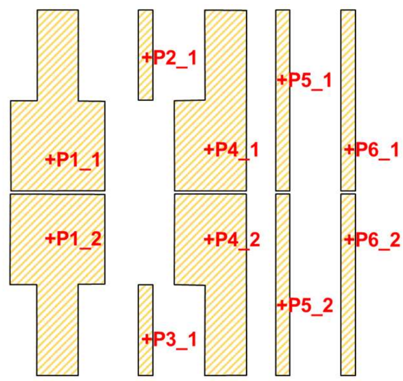

Fig. 2. Illustration of dividing a long or wide metal polygon into smaller segments and assigning a unique identifier to each segment to avoid duplicate calculations.

II. Methodology

To address the issue of inaccurate CDs in wafers caused by traditional rule-based formulas and the challenges of 2.5D R/C extraction, we present a CNN-based modeling flow (as depicted in Fig. 1). To capture the physical metal contours on wafers, our approach involves the preparation of a training dataset consisting of 20,000 pairs of drawn and simulated wafer images from advanced node with sub-nm resolution. A field-of-view (FOV) is designed with an area of 2 µm × 2µm to facilitate efficient training. In practical layout designs, metal polygons frequently extend beyond the FOV, which can adversely affect the accuracy of RC extraction. To mitigate

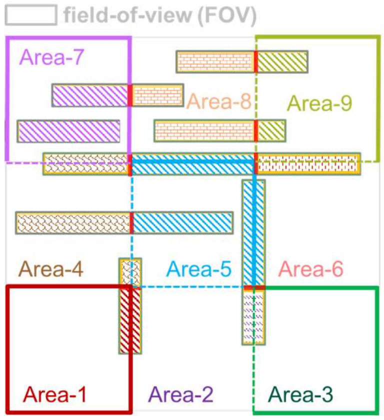

Fig. 3. Illustration of partial capacitance extraction by scanning the entire layout with a fixed FOV. In this example, there are 9 FOVs.

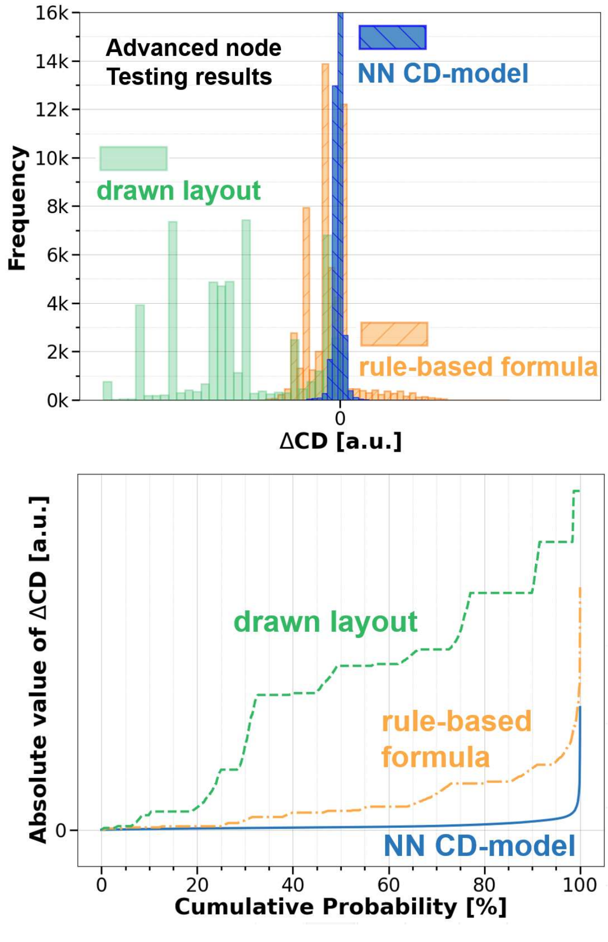

Fig. 4. (a) ΔCD distribution comparison among drawn, rule-based, and NN CD-models (using simulated wafer contours as the reference), and (b) its corresponding cumulative probability.

this issue, we divide long/wide metal polygons into smaller segments (as shown in Fig. 2) and compute the R/C values for each segment. The overall R/C of the targeted metal polygon is then obtained by summing the R/C values of all segments. By repeating this process and traversing the entire layout with a fixed FOV, we can determine the R/C values for all metal polygons (Fig. 3). This approach facilitates the preparation and extraction of the training dataset using the commercial 3D field solver tool. With this comprehensive training dataset, we can effectively train our CNN models for CD and R/C

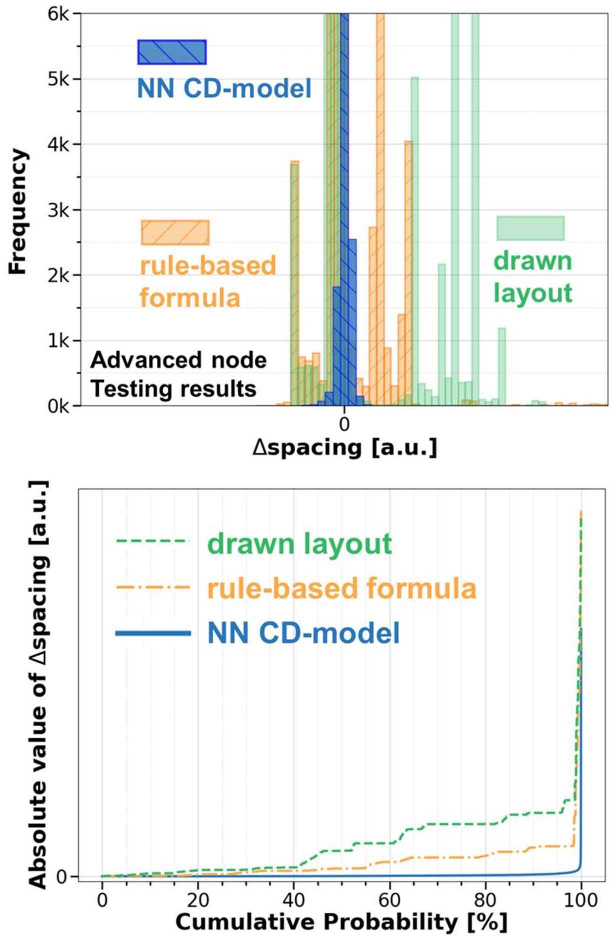

Fig. 5. (a) Δspacing distribution comparison among drawn, rule-based, and NN CD-models (using simulated wafer contours as the reference), and (b) its corresponding cumulative probability.

prediction by employing the mean square error (MSE) loss function.

III. Result and Discussion

Fig. 4(a) presents a comparison of accuracy in metal CD between the rule-based formula and our NN CD-model. Although the rule-based formula provides some improvements in reducing ΔCD offsets, our NN CD-model achieves an even more significant reduction. The corresponding cumulative probability plot for CD is shown in Fig. 4(b). Notably, our NN-CD model is capable of predicting not only metal CDs but also metal spacings. As illustrated in Fig. 5, the metal spacing predictions from our NN CD-model outperform those of the traditional rule-based formula. In other words, compared to traditional rule-based wafer CD models, our NN CD-model offers superior accuracy for both metal CD and spacing, i.e. it effectively captures the physical metal contour on the wafer. As a result, with precise predictions of physical wafer contour, our NN RC-model can accurately predict inter-layer capacitance for single layers and cross-layer capacitance for multiple layers of Si. Fig. 6(a) evaluates the accuracy of parasitic capacitance predictions made by our NN RC-model compared to the commercial 3D field solver. The results demonstrate that the parasitic capacitance predicted by the NN RC-model (C_NN) closely matches the capacitance extracted by the commercial 3D field solver (C_3D). The benchmark between the NN RC-model and commercial 2.5D RC tool, depicted in Fig. 6(b), shows

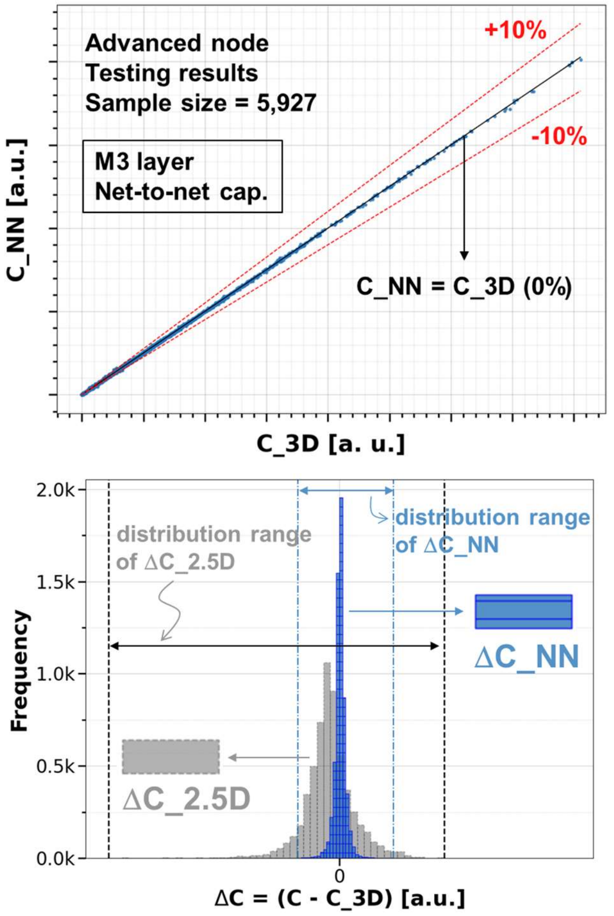

Fig. 6. (a) Evaluation of NN RC-model for parasitic capacitance of single M3-layer, and (b) ΔC distributions comparing the NN RC-model and 2.5D tool (using 3D field solver results as a reference).

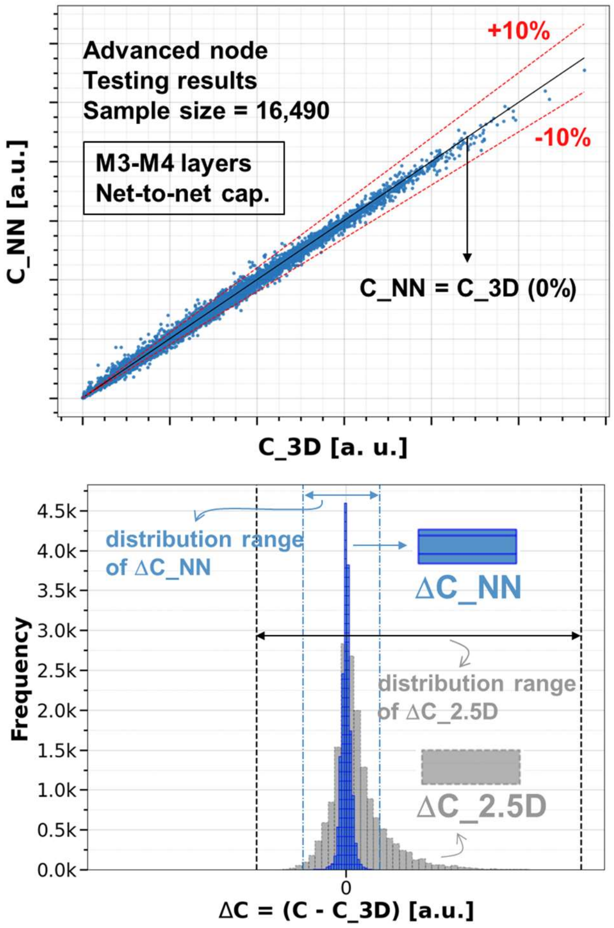

Fig. 7. (a) Evaluation of NN RC-model for parasitic capacitance of multiple M3-M4 layers, and (b) ΔC distributions comparing the NN-RC model and 2.5D tool. The NN RC-model remains closely aligned with the 3D tool and offers better accuracy than the 2.5D tool.

that the ΔC distribution of NN RC-model is significantly narrower than that of 2.5D tool counterpart. A similar trend can be observed for cross-layer coupling capacitance, as shown in Fig. 7. In the analysis of cross-layer capacitance for multiple layers, our NN RC-model consistently delivers superior prediction results compared to 2.5D rule-based RC tool, achieving accuracy comparable to 3D field solver. This suggests that machine-learning techniques, such as our NN model, are more effective than traditional rule-based approaches for parasitic capacitance extraction.

Beyond parasitic capacitance, our NN RC-model also demonstrates high accuracy in predicting parasitic resistance. Fig. 8 compares the parasitic resistance accuracy across our NN-RC model, the 2.5D RC tool, and the 3D field solver. As shown in Fig. 8(a), our NN RC-model achieves remarkable accuracy in predicting parasitic resistance, aligning closely with commercial 3D field solver (i.e., R_NN ≈ R_3D). The ΔR distribution, shown in Fig. 8(b), demonstrates that the variation range of NN RC-model is comparable to that of commercial 2.5D tool. In addition to the metal CD, another key factor influencing parasitic resistance is metal density, as variations in density lead to changes in metal thickness. In this context, metal density is defined as the percentage of the area covered by metal polygons within a fixed size of 40μm × 40μm. Fig. 9 presents a comparison of resistance accuracy across different density levels between the NN-RC model and the 3D field solver. The result demonstrates that the NN-RC model effectively captures the relationship between parasitic resistance and density with a high degree of accuracy. Notably,

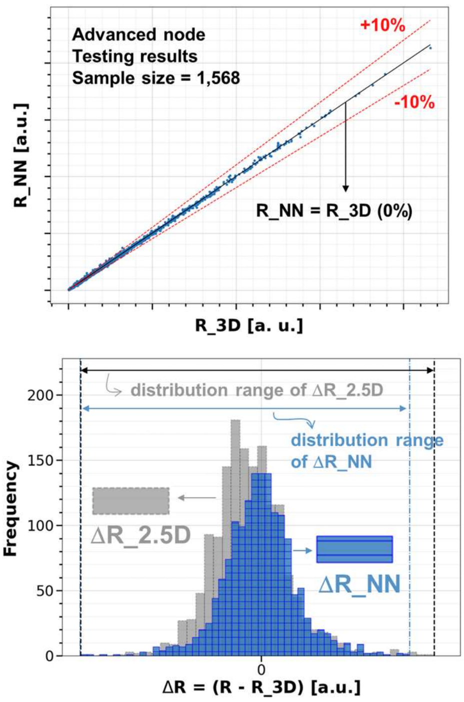

Fig. 8. (a) Evaluation of NN RC-model for parasitic resistance, and (b) ΔR distributions comparing the NN RC-model and 2.5D tool. R_NN and R_3D denotes the resistance extracted by the NN RC-model and 3D field solver, respectively.

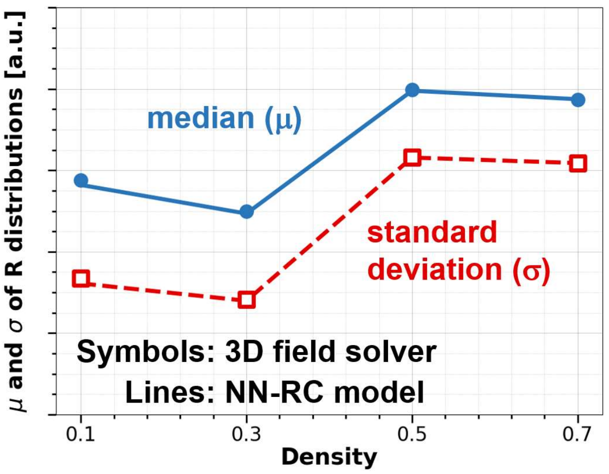

Fig. 9. Comparison of the predicted median (μ) and standard deviation (σ) from the NN-RC model with varying densities, benchmarked against the 3D field solver tool. Here, density is defined as the percentage of the area covered by metal polygons within a fixed size of 40μm × 40μm. Sample points for density include values of 0.1, 0.3, 0.5, and 0.7.

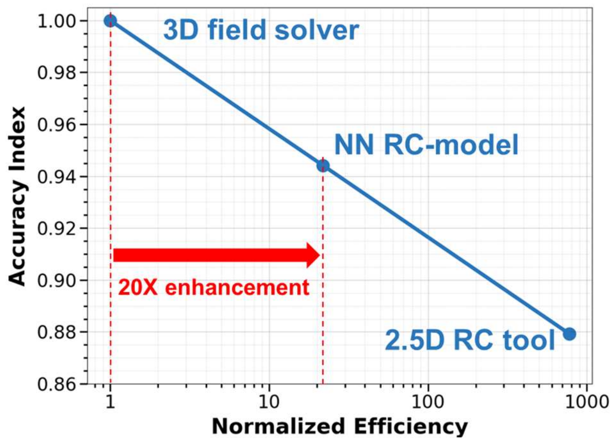

Fig. 10. Comparisons of accuracy and efficiency across the 3D field solver, 2.5D rule-based RC tool, and our NN RC-model. The accuracy index is defined as the average R^2 value obtained from 28 GDS layouts.

the observed non-monotonic trend arises from the fact that metal thickness does not scale linearly with density.

In addition to accuracy, efficiency is also crucial for parasitic R/C extraction. Fig. 10 compares the accuracy and efficiency of the 3D field solver, the 2.5D rule-based RC tool, and our NN RC-model. It can be found that our NN RC-model achieves a 20X improvement in efficiency over the 3D field solver, while simultaneously delivering higher accuracy than the 2.5D RC tool.

With the well-developed NN CD- and RC-models, the feasibility of an electrical-aware co-optimization from layout design to final electrical performance can be manifested. Fig. 11 illustrates the concept of the CNN-based electrical-aware pattern optimization flow. Please note that one of the primary objectives of this paper is to demonstrate the potential of AI techniques in advancing BEOL modeling for the community.

IV. Conclusion

We have developed a contour-driven solution for BEOL R/C extraction using a CNN-based algorithm. Our NN CD-model well predicts metal contour, outperforming

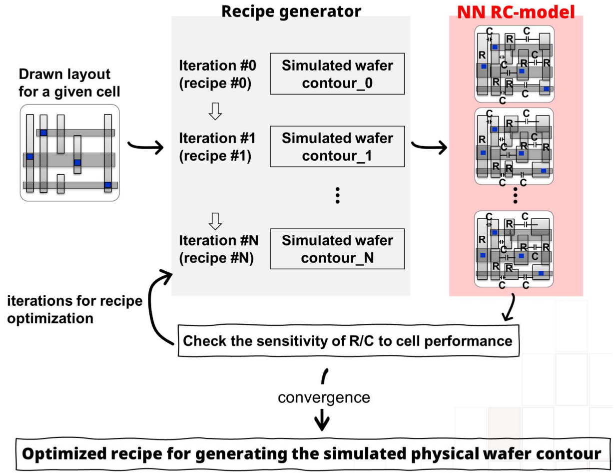

Fig. 11. A flowchart of the electrical-aware pattern optimization for advanced nodes. With the NN-RC model, it is promising to achieve the co-optimization from layout design to final electrical performance.

conventional rule-based methods and thus effectively reducing the Si-to-Simulation (S2S) gap. Our NN-RC model demonstrated a new approach with a favorable balance between accuracy and efficiency. It provides superior R/C predictions and efficiency at the same time compared to the existing solutions. Consequently, the co-optimization of layout and electrical performance is feasible for the first time under this solution. Our study explores the potential of advanced AI models in parasitic RC modeling for the BEOL community. Enhanced collaboration between the foundry and EDA partners is crucial to integrate these innovations into industrial production flows.

References

[1] C. Venkataiah, K. Satya Prasad, and T. Java Chandra Prasad, "Effect of interconnect parasitic variations on circuit performance parameters," *Proc. Int. Conf. Commun. Electron. Syst. (ICCES)*, 2016, pp. 1–4.

[2] W. Yu, M. Song, and M. Yang, "Advancements and challenges on parasitic extraction for advanced proccess technologies," *2021 26th Asia and South Pacific Design Automation Conf. (ASP-DAC)*, Tokyo, Japan, 2021, pp. 841–846.

[3] J. H.-C. Chen, T. E. Standaert, E. Alptekin, T. A. Spooner, and V. Paruchuri, "Interconnect performance and scaling strategy at 7 nm node," in *Proc. IEEE Int. Interconnect Technol. Conf.*, San Jose, CA, USA, 2014, pp. 93–96.

[4] D. Yang, W. Yu, Y. Guo and W. Liang, "CNN-cap: effective convolutional neural network based capacitance models for full-chip parasitic extraction," *2021 IEEE/ACM Int. Conf. on Computer-Aided Design (ICCAD)*, Munich, Germany, 2021, pp. 1–9.

[5] M. S. Abouelyazid, S. Hammouda, and Y. Ismail, "Accuracy-based hybrid parasitic capacitance extraction using rule-based, neural-networks, and field-solver methods," *IEEE Trans. Comput. Aided Design Integr. Circuits Syst.*, vol. 41, no. 12, pp. 5681–5694, Dec. 2022.

[6] Z. Li and W. Shi, "Layout capacitance extraction using automatic pre-characterization and machine learning," *2020 21th Int. Symp. on Quality Electronic Design (ISQED)*, Santa Clara, CA, USA, 2020, pp. 457–464.

[7] R. R. Chauhan, K. K. Ghanshala, and R. C. Joshi, "Convolutional neural network (CNN) for image detection and recognition," *2018 1st Int. Conf. Secure Cyber Comput. Commun. (ICSCCC)*, Jalandhar, India, 2018, pp. 278–282.

[8] J. Naranjo-Torres, M. Mora, R. Hernández-García, R. J. Barrientos, C. Fredes, and A. Valenzuela, "A review of convolutional neural network applied to fruit image processing," *Appl. Sci.*, vol. 10, no. 10, p. 3443, May 2020.