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Design, Simulation, Fabrication, and Parametric Optimization of Microstrip Antennas Using Deep Learning Algorithms

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Abstract - Designing a microstrip patch antenna still means running an EM simulation, adjusting the dimensions by hand, and running it again. That works for a simple rectangular patch, but the cost grows quickly once the geometry or the specifications get more demanding. This review looks at how deep learning (DL) and machine learning (ML) have been used at each stage of that workflow, from design to simulation, fabrication, and optimization. It draws on four studies: a decision tree combined with a fuzzy inference system for classifying antennas and predicting their parameters; a dual-band design study using multi-output regression and a residual network; an artificial neural network (ANN) framework for optimizing 5G smart antennas; and a PRISMA-based survey of ML/DL work in antenna engineering. The paper is organized in the order a designer would work through the problem. It starts with design basics and the generation of datasets from EM simulations, then covers forward and inverse DL models, followed by parametric-optimization case studies with a comparison between them, and finally fabrication and measurement. One thing stands out across all the studies: none of them checks its DL predictions against a fabricated, measured antenna. Every result stays in simulation. We treat this as the main open problem and propose a six-stage DL-assisted design–simulation–fabrication framework aimed at closing that gap.

Key Words: deep learning, microstrip antenna, antenna parameter estimation, dual-band antenna, 5G antenna, parametric optimization, antenna fabrication

1. INTRODUCTION

Microstrip patch antennas are among the most widely deployed radiating structures in modern wireless systems, valued for their low profile, light weight, planar geometry, and compatibility with standard printed-circuit-board (PCB) fabrication processes. These properties make them the default choice for 5G sub-6 GHz and mm-wave terminals, Internet-of-Things (IoT) nodes, wireless body area networks, and satellite communication front-ends. The electrical behavior of a microstrip antenna — its resonant frequency, reflection coefficient (S11), bandwidth, gain, and radiation pattern — is governed by a set of interacting geometric and material parameters, including patch length and width, substrate height and permittivity, feed position, and any slots or parasitic elements used to enable multi-band operation.

The conventional route to a working microstrip antenna involves four broadly sequential stages: analytical sizing using transmission-line or cavity-model equations; electromagnetic (EM) simulation and parametric tuning in tools such as CST, HFSS, FEKO, or ADS; fabrication of the tuned design on a substrate such as FR-4 or Rogers laminate; and measurement with a vector network analyzer (VNA) to confirm that the fabricated prototype matches the simulated performance. Each of these stages is time-consuming in isolation, and the loop between them is typically iterative — a mismatch discovered at fabrication or measurement often forces a return to the simulation stage, and a change to one geometric parameter frequently requires re-running a full-wave simulation before its effect on performance is known. As antenna topology complexity grows — for dual-band, multiband, or array configurations — the number of design variables and the corresponding simulation burden increase sharply.

Deep learning (DL) offers a way to shorten this cycle by learning the underlying nonlinear relationship between antenna geometry and electromagnetic performance directly from data, rather than re-deriving it from first principles for every candidate design. Once trained on a dataset of geometries and their simulated (or measured) responses, a DL model can be used in two directions: as a forward model, predicting performance from a given geometry, or as an inverse model, estimating the geometry required to meet a target performance specification. Both directions have been demonstrated for microstrip and related planar antennas using algorithms ranging from decision trees and fuzzy inference systems to support vector machines, ensemble regressors, and residual neural networks.

This review examines how DL algorithms are being applied across the full design–simulation–fabrication–optimization pipeline for microstrip antennas, using four representative studies as its technical basis: a decision-tree-plus-fuzzy-inference-system (DT+FIS) framework for antenna classification and geometric parameter prediction; a comparative deep-learning study of SVM, regressor neural networks, and Residual Neural Networks (ResNet) for multi-output dual-band antenna design; an ANN-based framework for optimizing 5G smart antenna parameters; and a comprehensive survey of ML/DL applications across antenna design, optimization, and selection. Rather than organizing the discussion by antenna sub-type, this review follows the sequence a designer actually moves through — design fundamentals, simulation-based dataset generation, DL modeling techniques, parametric optimization, and fabrication/validation — so that the gaps identified at each stage motivate a unified framework directly applicable to the present project.

2. MICROSTRIP ANTENNA DESIGN FUNDAMENTALS

Basic structure. A microstrip patch antenna consists of:

- A conducting radiating patch on top of a dielectric substrate (thickness h, permittivity ε_r)
- A ground plane on the bottom face
- The rectangular patch in its dominant TM_{010} mode is the baseline case used across the reviewed literature

Governing equations.

Patch width sets radiation resistance and bandwidth:

$W = c / (2f_r) \sqrt{(2 / (\varepsilon_r + 1))}$

Fringing fields make the patch behave as an effective medium:

$\varepsilon_{eff} = (\varepsilon_r + 1)/2 + ((\varepsilon_r - 1)/2) [1 + 12h/W]^{-1/2}$

The patch is electrically longer than its physical length by an extension ΔL per edge, so:

$L = L_{eff} - 2\Delta L, \quad L_{eff} = c / (2f_r\sqrt{\varepsilon_{eff}})$

The same underlying logic — resonant length scaled by ε_eff rather than free-space wavelength alone — underlies the monopole formula used in the dual-band case study:

$f_{c1} = c / (4L_{TR}\sqrt{\varepsilon_{eff}})$

Feed mechanisms. Four standard options, trading fabrication complexity against bandwidth and matching flexibility:

- **Inset feed** — notch cut into the patch edge for direct 50 Ω matching without an external transformer; the feed type used in the DT+FIS classification study
- **Coaxial probe feed** — simple to fabricate, but adds inductance that degrades matching as substrate thickness increases
- **Aperture-coupled feed** — feed line and patch on separate layers, coupled through a ground-plane slot; isolates feed-network radiation but requires multilayer fabrication
- **Proximity-coupled feed** — feed line and patch on separate layers with no slot; widest achievable bandwidth of the four, but most alignment-sensitive

Design-variable growth.

- A single-band patch is fully specified by (*L, W, h, ε_r*, feed position)
- Multiband designs add resonant elements, each with independent geometry
- The dual-band case study illustrates this directly: a baseline quarter-wave monopole (*L_TR, W_TR, W_sub, L_gnd*) is augmented with an L-shaped coupled strip to produce a second band, adding five further variables (*L_v, L_h, s, d_offset, W_v, W_h*) — more than doubling the parameter count for one additional resonance

Why this matters going forward.

- The equations above are first-order estimates only — they ignore coupling, loss tangent, and finite ground-plane effects
- Even a single-band design needs EM-solver refinement to hit target *S11*, bandwidth, and gain
- For coupled multi-element geometries (dual-band, multi-band), no closed-form equivalent exists at all — the only route to a geometry–performance mapping is repeated full-wave simulation
- This is the specific gap Section 4's DL surrogate models are built to close

3. ELECTROMAGNETIC SIMULATION AND DATASET GENERATION

The core problem. No standard, reusable antenna datasets exist for most topologies, so nearly every DL-based antenna study generates its own — confirmed as a field-wide pattern by the broader survey underlying this review.

General workflow.

- Derive an initial geometry from the closed-form equations covered in Section 2
- Identify which parameters most strongly affect the target response
- Sweep only those parameters in a full-wave EM solver (CST, HFSS, FEKO, or IE3D)
- Produce a labeled set of geometry–performance pairs

Constraining the sweep.

- Sweeping every design variable independently is combinatorially infeasible
- The DT+FIS classification study addresses this with a control-variate approach: prior analytical formulae are used first to identify which parameters materially affect each antenna type's *S11*, gain, bandwidth, and resonant frequency, and only those are varied in HFSS
- This yielded roughly 50 simulated samples per antenna class (150 total across microstrip, horn, and helical types)
- Small by ML standards, but consistent with the field: the broader survey's dataset table shows reviewed studies ranging from 80 to about 1,267 samples

Extraction and cleanup.

- Raw solver output is not directly usable as training data
- The dual-band regression study generated 1,000 CST samples (700 train / 300 test) by exporting *S11* from auto-generated .s1p files and VSWR from .txt files
- A MATLAB post-processing step then extracted the actual modeling features — operating frequency, bandwidth, minimum *S11*, and VSWR at that frequency — rather than using raw frequency-swept curves directly
- This extraction step is easy to overlook but is where most of the feature-engineering work actually happens

A different data source.

- Not every dataset in this space comes from EM simulation
- The 5G smart-antenna study instead manually collected 1,000 operational samples — antenna angle, signal strength, interference level, transmission speed, coverage area, efficiency
- This reflects a deployment-level dataset, not a geometry-level one
- It optimizes operating parameters of an already-fabricated smart antenna system rather than physical dimensions of a patch, and does not fit the geometry→performance mapping the rest of this review is built around

Implication for dataset size.

- Across the reviewed case studies and the wider survey, simulated antenna datasets are consistently small (order of 10^2–10^3 samples)
- Each additional sample costs a full-wave simulation run that can take minutes to hours depending on structure complexity
- This constraint is directly relevant to the near-zero error metrics flagged as a possible overfitting risk in Section 5: a few hundred samples provides limited coverage of the design space, and low reported error on a held-out split from the same small, correlated dataset is a weaker generalization signal than it appears

4. DEEP LEARNING ALGORITHMS FOR ANTENNA PARAMETER MODELING

Two directions of modeling:

- **Forward model** — geometry → performance (resonant frequency, *S11*, bandwidth, gain). Replaces a full-wave simulation with a fast inference step.
- **Inverse model** — target performance → geometry. Harder, because multiple geometries can produce similar electromagnetic responses (one-to-many, not one-to-one).

Three modeling approaches found across the case studies:

4.1. Classification followed by regression

- Stage 1: a decision tree classifier identifies antenna type/topology from electromagnetic indicators (gain, bandwidth, resonant frequency)
- Stage 2: a fuzzy inference system, conditioned on the classified type, predicts geometric parameters as fuzzy membership functions rather than point estimates
- Suits problems where a labeled dataset spans genuinely distinct antenna families

4.2. Multi-output regression / residual networks

- Predicts several coupled geometric parameters jointly in a single model, rather than training a separate regressor per output
- Captures inter-output correlations that independent single-output models ignore — relevant when parameters are physically coupled (e.g., a second-band strip geometry dependent on a first-band monopole)
- Residual (skip-connection) architectures extend this further: they learn the residual mapping rather than the full transformation, converging faster and generalizing more consistently as the number of predicted outputs grows
- Suits a single antenna family with several interdependent design parameters

4.3. Plain ANN regression

- Standard feedforward network: a few hidden layers, ReLU activations, linear output, trained with MSE loss
- Effective when the input–output relationship is smooth and features are well-chosen
- No architectural mechanism for handling heterogeneous design spaces (no sub-type awareness, no residual structure) — performance depends more on dataset and feature engineering than on the architecture itself
- Reasonable default when neither of the above two conditions clearly applies

5. PARAMETRIC OPTIMIZATION USING DEEP LEARNING

5.1. Classification-guided optimization

- Select antenna topology first, then optimize that topology's parameters with a model tuned specifically to it
- Narrows the search space before optimization begins
- Limitation: depends on labeled data across every candidate topology; does not help within a single fixed topology

5.2. Direct multi-parameter regression optimization

- Maps desired multi-band performance targets (frequency, bandwidth, *S11*, VSWR per band) directly onto the full geometric parameter set.
- Closer to true inverse design — produces a usable geometry, not just a performance estimate
- Limitation: output parameters have uneven sensitivity to inputs. Strongly-correlated dimensions (e.g., overall substrate size) predict with low error; weakly-correlated dimensions (spacing, offset parameters) carry substantially higher error

5.3. ANN-based operational optimization

- Optimizes operating parameters of a deployed smart antenna (angle, gain settings) from signal/environment data, not physical geometry
- Treats hardware as fixed; optimizes configuration rather than dimensions
- A meaningfully different target from pipelines 1 and 2

Comparative summary:

Table -1: Comparative summary of the three parametric-optimization case studies

Antenna type(s)	DL/ML method	Optimization target	Dataset size	Reported accuracy	Key limitation
Microstrip patch, horn, helical	Decision Tree classifier + Fuzzy Inference System	Geometric parameters, conditioned on classified antenna type	~150 samples (50/class)	Classification accuracy >99%; MAPE <5.8%	Small per-class sample size; near-zero error on some outputs suggests possible overfitting

Antenna type(s)	DL/ML method	Optimization target	Dataset size	Reported accuracy	Key limitation
Dual-band L-strip monopole	Fine Gaussian SVM, multi-output regressor NN, ResNet	Ten coupled geometric parameters across two bands	1,000 samples (700/300 split)	ResNet average error ≈1.2–1.3% vs. 7–8% for single-output models	Error highly uneven across outputs; weakly-correlated parameters (e.g., strip offset) far less accurate
5G smart antenna (operational)	ANN (8 inputs, 3 hidden layers)	Operating parameters (beamwidth, gain-related settings) from environmental/signal inputs	1,000 manually collected samples	$R^2 \approx 0.9999999999998$; RMSE $\approx 5.26\times10^{-6}$	Operational, not geometric, optimization; reported error implausibly low for the stated methodology

Two patterns across all three:

- Dataset size is the binding constraint regardless of pipeline — none exceeds 1,000 samples; one uses only 50 samples per class
- Reported accuracy near the numerical noise floor (MAPE ≈0%, R^2 at 13 nines) is more consistent with a small, correlated dataset and possible overfitting than with genuinely near-perfect modeling — flagged here rather than taken at face value

6. FABRICATION AND EXPERIMENTAL VALIDATION

The core finding. None of the three design/optimization case studies validates its predictions against a fabricated, measured prototype:

- The classification-and-fuzzy-inference study trains and tests entirely on HFSS-generated data
- The dual-band regression study trains and tests entirely on CST-simulated *S11* and VSWR
- The 5G operational-optimization study uses manually collected but still simulation-adjacent data — no fabricated hardware in the loop

The broader survey underlying this review confirms this is a field-wide pattern, not an isolated gap: commercially deployed antennas that openly use ML/DL in their design process remain rare, and the simulation-to-measurement gap is flagged as a standing open challenge for the field as a whole.

Why the gap matters:

- A DL model is only as accurate as the physics in the solver that generated its training data
- EM solvers idealize: lossless/simplified boundary conditions, ideal feed excitation, exact permittivity values
- Fabrication introduces discrepancies a simulation-only model never sees in training — manufacturing tolerance, batch-to-batch substrate permittivity variation, connector/solder parasitics, defects at fine features (narrow slots, tight spacing)
- Near-zero error rates reported in Section 5 are therefore only evidence of fit to simulated data — they say nothing about measured-hardware accuracy

What this caps. A model in this literature can be validated as an accurate surrogate for an EM solver — a real and useful result — but not yet as an accurate predictor of physical antenna behavior, since that claim requires a measurement step none of the four papers takes. Closing it requires either:

- Augmenting simulated training data with measured samples so the model learns the sim-to-measured correction, or
- At minimum, treating DL-predicted geometries as fabrication candidates rather than final designs

Relevance to the present project. The project's scope — design, simulation, fabrication, and parametric optimization — is positioned to close exactly this loop: fabricate a DL-predicted/optimized geometry and measure it against both the simulated prediction and the design target. That simulated-vs-measured (and by extension DL-predicted-vs-measured) comparison is the concrete contribution angle this review has been building toward, and it should carry directly into the project's methodology chapter.

7. RESEARCH GAPS AND CHALLENGES

7.1. Dataset scarcity and inconsistency

- All three case studies operate on small datasets (50–1,000 samples); the survey confirms this is field-wide, with reviewed datasets ranging roughly 80–1,267 samples
- No standardized antenna datasets exist across the field — every study generates its own via simulation or manual collection, with no shared benchmark for comparing methods
- Small sample sizes, combined with near-zero reported error in some studies, point toward likely overfitting rather than genuine generalization

7.2. Simulation-to-measurement gap

- Carried forward from Section 6: no case study validates against fabricated hardware
- EM solvers idealize boundary conditions, feed excitation, and material properties in ways that do not transfer exactly to physical fabrication
- This is the specific gap the present project's fabrication scope is positioned to close

7.3. Uneven prediction accuracy across coupled outputs

- In the dual-band multi-output regression case study, parameters weakly correlated with the model inputs (strip spacing, feed offset) are predicted far less accurately than strongly correlated ones (overall substrate dimensions)
- This is a structural limitation of treating geometrically coupled parameters as a flat output vector, not just a data quantity issue

7.4. Non-uniqueness of inverse design

- Multiple distinct geometries can produce near-identical electromagnetic responses, so inverse models (performance → geometry) are inherently ill-posed
- None of the reviewed studies addresses this directly — each reports single-point predictions rather than a distribution or candidate set of plausible geometries

7.5. Narrow scope per model

- Each case study is built for one antenna family (microstrip+horn+helical classification; a single dual-band L-strip geometry; one 5G operational setup) rather than a topology-agnostic approach
- The classification-then-fuzzy-inference pipeline partially addresses this but still requires labeled data for every antenna family included, so it does not generalize to unseen topologies

Where this leaves the field, and this project. These five gaps are not independent — dataset scarcity is partly what drives uneven output accuracy and prevents robust handling of inverse non-uniqueness, and the absence of measured data means even a well-fit simulation model carries unverified real-world accuracy. The project's design–simulation–fabrication–optimization scope directly addresses the second gap, and its focus on a single microstrip family with coupled parameters (dual-band or multi-band) puts all other gaps squarely in scope for the methodology chapter rather than being left as future work.

8. PROPOSED DL-ASSISTED DESIGN–SIMULATION–FABRICATION FRAMEWORK FOR MICROSTRIP ANTENNAS

Drawing together the approaches surveyed earlier and the gaps identified in the previous section, this section proposes a framework structured around the project's own four phases, rather than around antenna sub-type.

Stage 1 — Analytical initialization (Design)

- Compute starting geometry from transmission-line/cavity-model equations: *W, L, ε_eff*, feed position
- Purpose: bound the EM-solver search space before any simulation is run, avoiding a blind parameter sweep

Stage 2 — Constrained dataset generation (Simulation)

- First identify which geometric parameters materially affect the target response — using prior analytical formulae to flag the influential variables before simulating, the way the DT+FIS study narrowed its HFSS sweep — rather than varying every design variable independently
- Generate geometry–performance pairs in the EM solver (CST/HFSS), extracting operating frequency, bandwidth, minimum *S11*, and VSWR — the post-processed figures of merit, not raw frequency-swept curves — as the modeling features
- Target a dataset large enough to address the dataset-scarcity gap: existing studies plateau at roughly 50–1,000 samples, so this stage should deliberately budget for a larger or more systematically stratified set, particularly across coupled parameters that tend to be predicted less accurately.

Stage 3 — Forward and inverse DL modeling

- Train a forward model (geometry → performance) as a validation baseline — this is the lower-risk, better-established direction of the two
- Train an inverse or joint forward/inverse model (performance → geometry) using a multi-output or residual-network regression approach, since the project's dual-band/multiband parameters are structurally similar to the L-strip coupling problem where several geometric outputs share dependence on the same inputs
- Explicitly report per-parameter error rather than only an averaged metric, so weakly-correlated outputs (e.g., spacing or offset parameters) are visible rather than masked by strongly-correlated ones (e.g., overall substrate dimensions)

Stage 4 — Optimization loop

- Use the trained model as a surrogate to search candidate geometries against target specifications, rather than re-running full EM simulation for every candidate — mirroring the direct multi-parameter regression optimization approach discussed earlier
- Where the inverse mapping is non-unique, generate a small set of candidate geometries per target rather than a single point prediction, and rank them by predicted proximity to spec before committing to fabrication

Stage 5 — Fabrication and measurement (the project's core contribution)

- Fabricate the top-ranked candidate(s) from Stage 4
- Measure *S11*, bandwidth, gain, and resonant frequency with a VNA
- Compare three-way: DL-predicted performance vs. CST-simulated performance vs. measured performance
- This three-way comparison is the step none of the four reference papers takes, and is what turns this from a simulation-only exercise into the design–simulation–fabrication–optimization pipeline the project title specifies

Stage 6 — Feedback (optional but recommended)

- If measured and simulated performance diverge meaningfully, feed the measured sample back into the training set as a correction point

- Even a handful of measured samples added to an otherwise simulation-trained dataset directly targets the simulation-to-measurement gap, rather than leaving it as an acknowledged but unaddressed limitation

Summary sequence: Analytical design → constrained EM dataset → forward/inverse DL model with per-parameter error reporting → surrogate-assisted optimization with candidate ranking → fabrication → measurement → three-way comparison → optional feedback into dataset.

This structure directly answers the dataset-scarcity, uneven-output-accuracy, and inverse-non-uniqueness gaps by construction, and treats the simulation-to-measurement gap not as a limitation to note in a conclusion, but as the framework's own final and defining stage.

9. CONCLUSION

This review examined four studies that together cover much of the ML/DL toolbox used in microstrip antenna design: a decision-tree-plus-fuzzy-inference framework for classification and parameter estimation, a multi-output regression and ResNet study of coupled dual-band geometry, an ANN-based study of operational optimization for 5G smart antennas, and a PRISMA-based survey of the wider field. Rather than grouping them by antenna type, the review followed the order in which a design project is actually carried out: design fundamentals, simulation-based dataset generation, DL modeling, parametric optimization, and fabrication and validation.

The main finding, is that none of the reviewed case studies checks its DL predictions against fabricated, measured hardware. The broader survey shows this is not a quirk of the three case studies. It is a pattern across the field.

A second finding is that many reported accuracy figures are too good to take at face value. MAPE values near 0% and R^2 values are more consistent with small, correlated datasets and possible overfitting than with a model that has captured antenna behavior almost perfectly. We flagged these figures throughout the review and did not treat them as settled results.

The proposed framework addresses both problems. It has six stages: analytical initialization, constrained dataset generation, forward and inverse DL modeling, surrogate-assisted optimization, fabrication and measurement, and an optional feedback stage. Its defining contribution is fabrication and measurement, where a single geometry is fabricated and its DL-predicted, EM-simulated, and VNA-measured performance are compared directly. Because this project covers fabrication and parametric optimization as well as design and simulation, it can make the comparison that the existing literature leaves out. The framework is intended to serve as the starting structure for the methodology chapter.

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REFERENCES

[1] R. Ramasamy and M. A. Bennet, "An Efficient Antenna Parameters Estimation Using Machine Learning Algorithms," Progress In Electromagnetics Research C, vol. 130, pp. 169–181, 2023.

[2] R. Gadhafi, A. Copiaco, Y. Himeur, K. Afsari, H. Mukhtar, K. Ghanem, and W. Mansoor, "Exploring the Potential of Deep-learning and Machine-learning in Dual-band Antenna Design," IEEE Open Journal of the Computer Society, 2024, doi: 10.1109/OJCS.2024.3463190.

[3] P. Kavitha and A. Thatikonda, "Optimizing 5G Smart Antenna Design Parameters using Deep Learning," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 22s, pp. 2073–2080, 2024.

[4] N. Sarker, P. Podder, M. R. H. Mondal, S. S. Shafin, and J. Kamruzzaman, "Applications of Machine Learning and Deep Learning in Antenna Design, Optimization and Selection: A Review," IEEE Access, vol. 11, pp. 103890–103915, 2023, doi: 10.1109/ACCESS.2023.3317371.