Project Presentation
on

Machine Learning Model To Predict Characteristics of GaN HEMT

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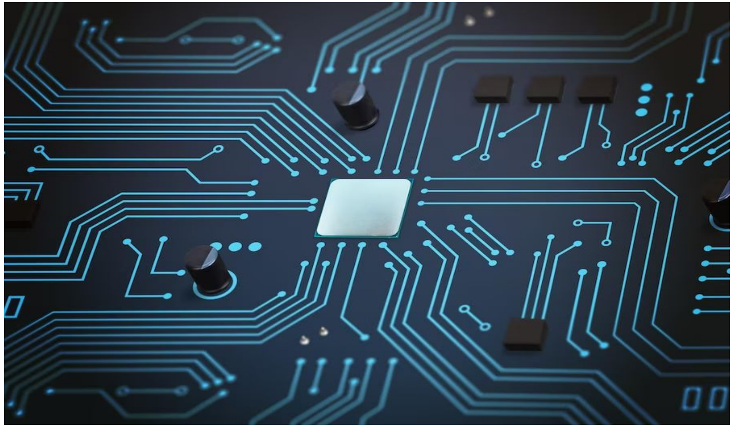
INTRODUCTION



- Gallium Nitride High Electron Mobility Transistors (GaN HEMTs) excel in diverse applications, benefiting from GaN's material properties and **heterostructure advantages**.
- GaN HEMTs are versatile devices used in power amplifiers, **high-frequency switches**, and sensors due to their material and electrical properties.
- GaN HEMTs are prized for their material advantages, including high electron mobility, making them invaluable in various electronic applications.

LITERATURE REVIEW

S.N.	Title	Year	Author	Description
1	Multi-output deep learning model for simultaneous prediction of figure of merits (Ion, Gm , and Vth) of gallium nitride high electron mobility transistors [1]	2022	Shivanshu Misha, Nidhi Chaturvedi	● Used **SPGDLF** approach which involves a two-stage training process for DL models. ● Used 9 model that are mobility, permittivity of AlGaN, thickness of AlGaN, unit gate width, gate length, distance from source to drain, gate to source voltage, threshold voltage, and drain to source voltage. ● The target variable for prediction is the **drain current** of GaN HEMTs ● A **multi-layer perceptron** (MLP) architecture was implemented for predicting the I-V characteristics. ● The input layer consists of nine parameters, and nonlinear regression is performed with a four-layer deep learning model, where the architecture is optimized through experimental evaluation.

LITERATURE REVIEW

S.N.	Title	Year	Author	Description
2	Prediction of threshold voltage of GaN HEMTs using deep learning model designed by genetic algorithm[2]	2022	Shivanshu Misha, Bipin Gaikwad, Nidhi Chaturvedi	• Genetic Algorithm for Hyperparameter Optimization • The input layer of the model consists of 3-dimensional vectors of Ion, Gm and SS. • Generated a dataset by simulating 2160 distinct GaN HEMT • The genetic algorithm optimizes six hyperparameters, including the number of layers, • The target variable for prediction is the threshold voltage of GaN HEMTs • predicts the threshold voltage of GaN HEMT devices with an average relative error of 2.61% and a standard deviation of 2.7%

LITERATURE REVIEW

S.N.	Title	Year	Author	Description
3	Semi-supervised physics guided deep learning framework: An application in modeling of gallium nitride based high electron mobility transistors [3]	2022	Shivanshu Misha, Bipin Gaikwad, Nidhi Chaturvedi	• Used GENERATIVE ADVERSARIAL NETWORK (GAN) model • The final GAN model is trained for 4000 epochs • Explored the minimum real data required to properly train the GAN model • Used a multi-output deep learning model which predicts multiple characteristics • Uses a four-dimensional input vector and employs Long Short-Term Memory(LSTM) layers • The model is trained for 1500 epochs using Adaptive Moment Estimation(ADAM) optimization.

LITERATURE REVIEW

S.N.	Title	Year	Author	Description
4	Modeling and parameter extraction method for AlGaN/GaN HEMT[4]	2018	A.Mishra, A.Khusro, M.S Hasami, A.Q Ansari	• Genetic Algorithm for Optimization • The input layer of the model consists of 3-dimensional. • Generated a dataset by simulating 3000 distinct GaN HEMT • The genetic algorithm optimizes 5 hyperparameters, including the number of layers, • The target variable for prediction is the threshold voltage of GaN HEMTs

Objective

- Generate a comprehensive dataset for GaN HEMTs using Silvaco TCAD (Technology Computer-Aided Design) software.
- Utilize this dataset to develop a robust Machine Learning model.
- The ML model will accurately predict GaN HEMT drain current.
- The primary goal is to significantly reduce the cost and time constraints associated with physical experimentation and simulation.

DATASET STRUCTURE AND FORMAT

The dataset selection for this project involved collecting a total of 3200 datasets, each comprising various input features . To ensure a robust machine learning model, the dataset was divided into two main subsets: a training set and a testing set.

In this partitioning, approximately 80% of the total datasets, which amounts to 2563 samples, were allocated for training the machine learning model. This training dataset was used to teach the model to understand the relationships between the input features and the corresponding 'Drain Current' values.

The remaining 20% of the datasets, totaling 641 samples, were reserved for testing the model's performance.

Drain to Source Voltage	V_{ds}
AlGaN thickness	t_{ox}
Gate Length	*l*
Gate Width	w
Drain Current	i_d

Table I:Parameters for ML model

Selection of the ML model

Data Selection:

- The dataset includes drain to source voltage, AlGaN thickness, gate length, gate width, and drain current due to their influence on drain current prediction.

Model Architecture:

- A neural network with 4 hidden neurons and a relu activation function was chosen for prediction of drain current.
- Exploration of different hidden neuron counts and activation functions may be considered for future model refinement.

ANALYZING MACHINE LEARNING MODEL :

- **Model Features**:
  - Utilizes features like drain to source voltage, AlGaN thickness, gate length, gate width, and drain current from the dataset.
  - Randomizes and normalizes dataset values for consistent input.
- **Model Architecture**:
  - Employs a neural network with layers having 20-20-10-10-1 neurons.
  - Applies the relu activation function to these neurons.
- **Training**:
  - Trains the model over 300 epochs for accurate sub-energy band level predictions.

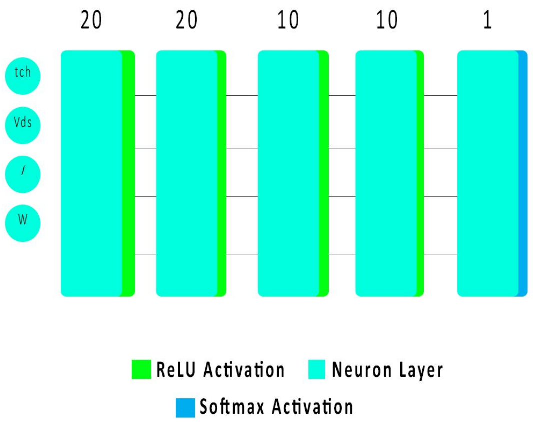


Fig. 1 Model Visual representation

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- **Model Persistence**:
  - Saves the trained model for future predictions using arbitrary data.
- **Training vs Validation Loss**:
  - Creates a Training vs Validation Loss plot to monitor model performance during training.
- **Prediction Process**:
  - Normalizes a new dataset to maintain consistency.
  - Passes the processed data through the saved model, generating predictions for sub-energy band levels.

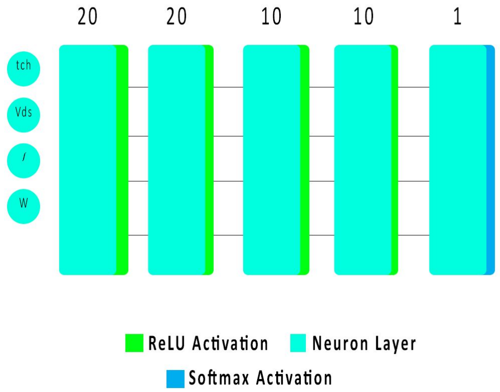
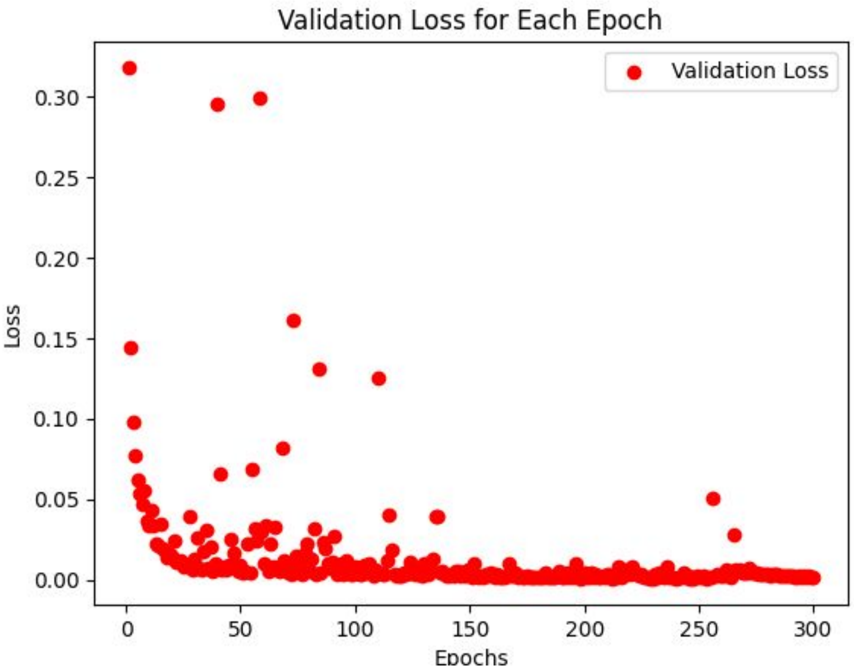


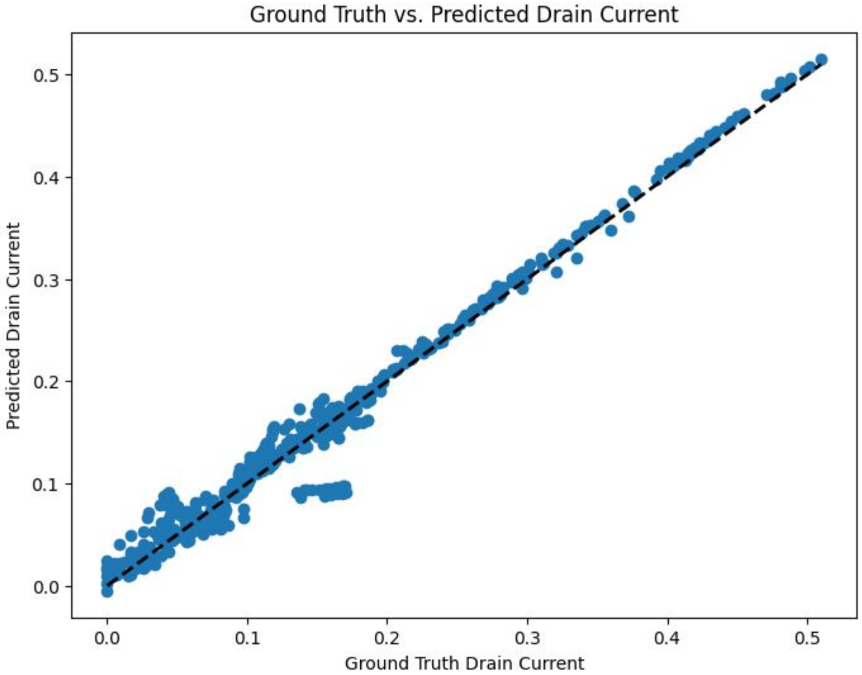
Fig. 1 Model Visual representation

Results

Fig I- Validation loss over epoch

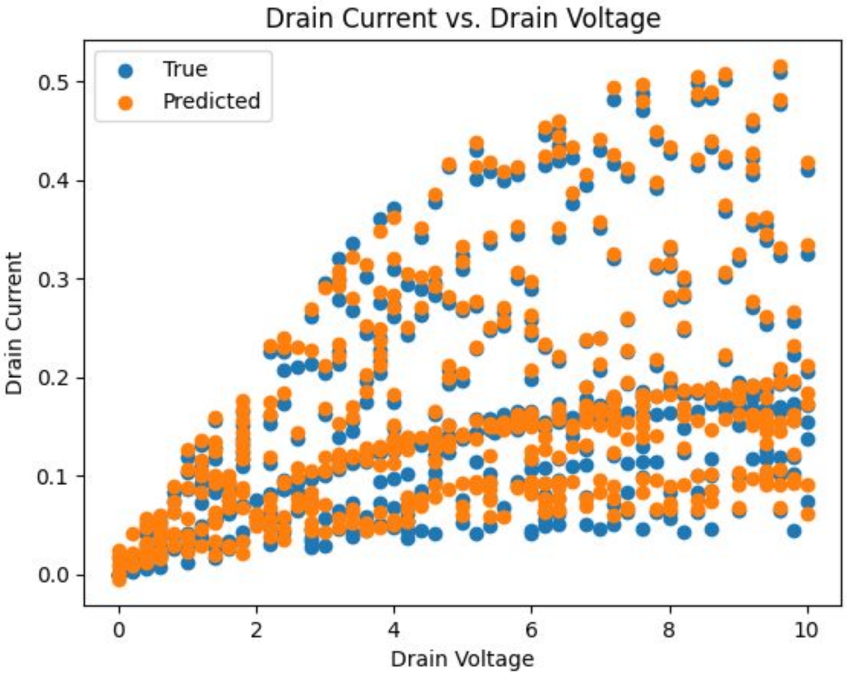
Fig II- Actual vs predicted drain current (Id in scale of 10E-1 A)

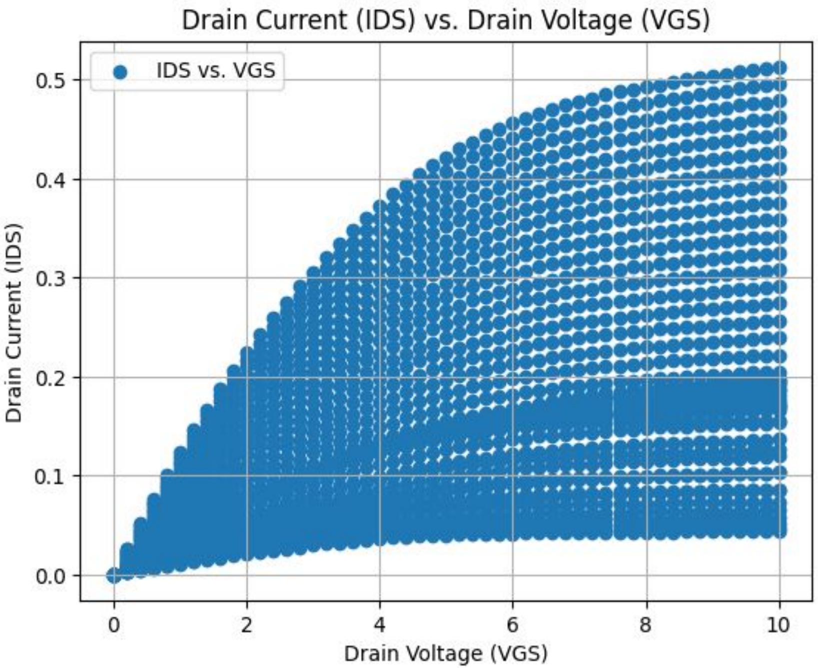




Results

Fig III- Drain current vs drain voltage for test dataset (Id in scale of 10E-1 A, Drain Voltage in volts)	Fig IV-Drain current vs drain voltage for whole dataset (Id in scale of 10E-1 A, Drain Voltage in volts)

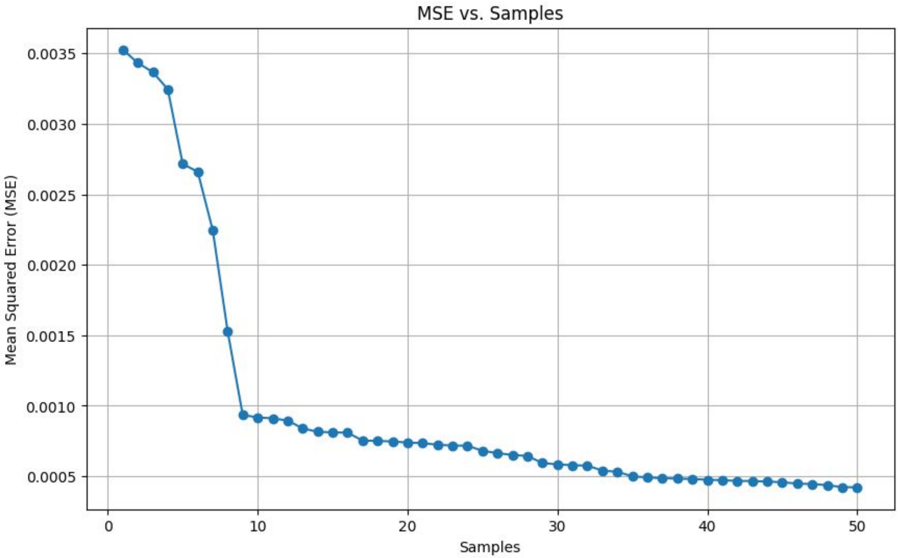


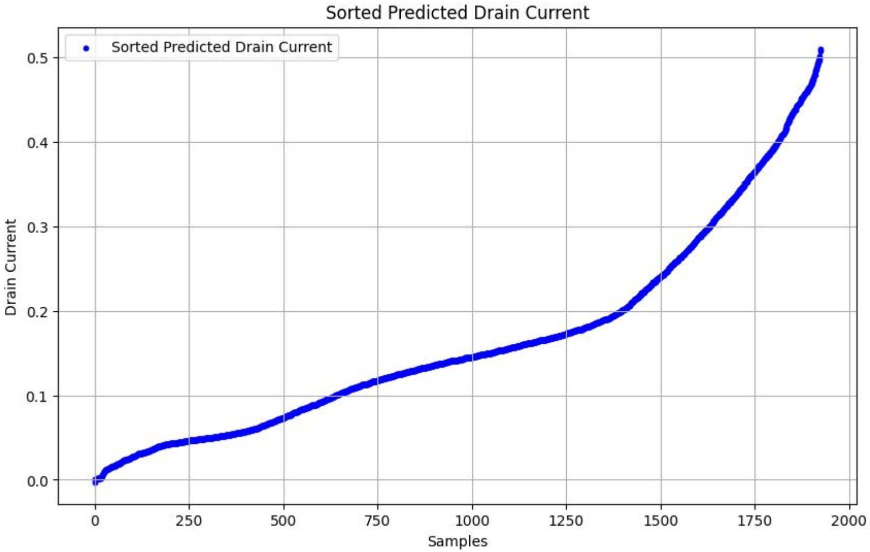


Results

Fig V- MSE vs samples

Fig VI- Variation of drain current with number of samples (Id in scale of 10E-1 A)

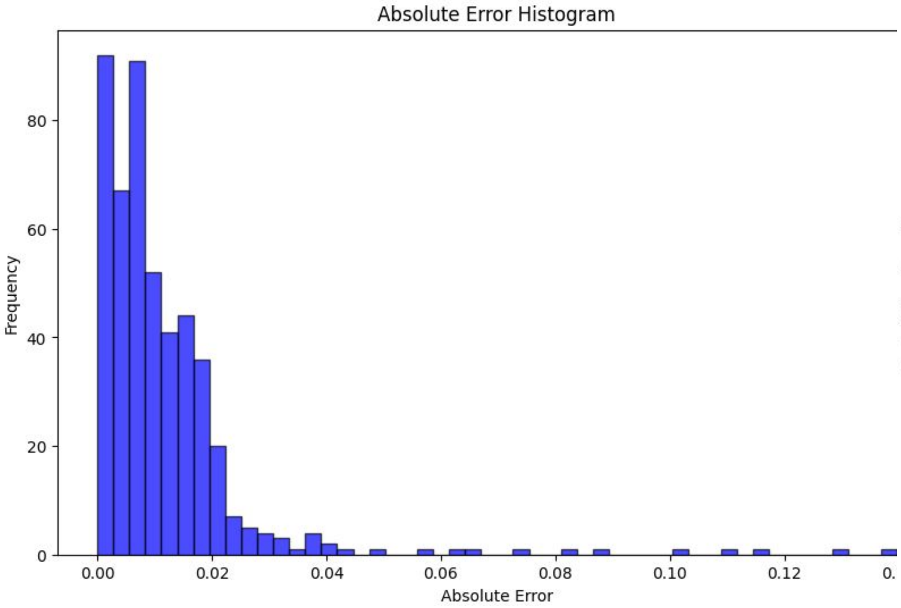


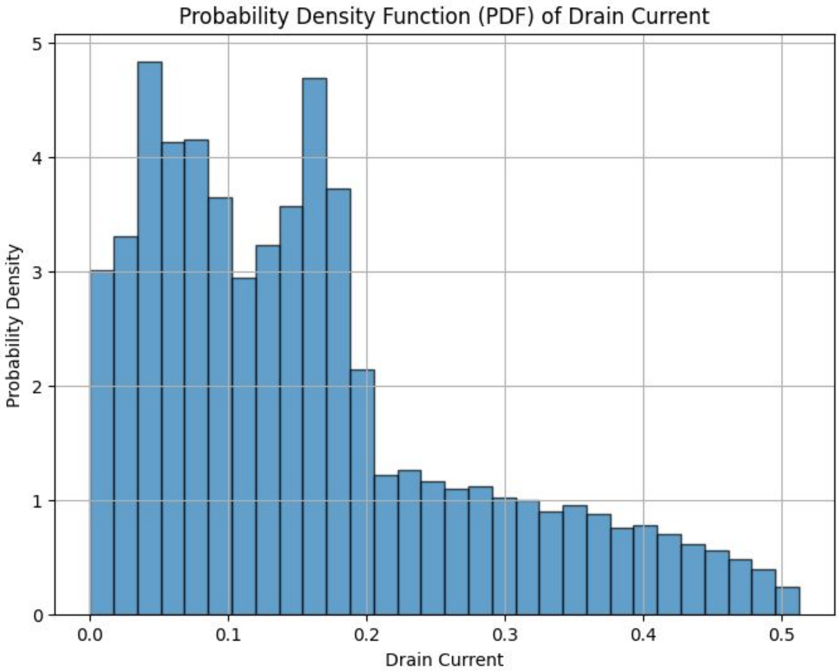


Results

Fig VII- Absolute error histogram

Fig VIII- Probability density function of drain current (Id in scale of 10E-1 A)





Analysis of the model

	R-squared	Mean Squared Error	Root Mean Squared Error
ML Model	0.9744170704726278	0.00033715694319545855	0.01836183387343046

Table 2: ML Model performance indexes

CONCLUSION AND FUTURE WORK

1. Accuracy Achievement: The project culminated in a remarkable 97.73% accuracy score.

2. Parameter Relationships: The model adeptly captures complex relationships between input parameters like drain voltage, gate thickness, gate length, and AlGan thickness, resulting in precise drain current predictions.

3. Industry Implications: The high accuracy holds substantial implications across various industries, facilitating refined semiconductor designs, optimized manufacturing processes, and reliable electronic systems in fields such as power electronics, telecommunications, and aerospace.

4. Path for Innovation: This success validates the machine learning approach, paving the way for further research in semiconductor technology. Leveraging this high-precision model opens avenues for innovation in electronics, communications, and beyond.

REFERENCES

1. Mishra, Shivanshu, and Nidhi Chaturvedi. "Multi-output deep learning model for simultaneous prediction of figure of merits (Ion, Gm, and Vth) of gallium nitride high electron mobility transistors." *Journal of Applied Physics* 131, no. 6 (2022).
2. Mishra, S., Gaikwad, B., & Chaturvedi, N. (2022). Prediction of threshold voltage of GaN HEMTs using deep learning model designed by genetic algorithm. *Materials Science in Semiconductor Processing*, *152*, 107057.
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