# B. TECH. PROJECT REPORT
# On

# ANN- Based Characterization of Wrinkling Instabilities in Soft Active Materials

BY
**Khushi Kumari (220003046)**
**&**
**Raja (220005041)**

**DISCIPLINE OF MECHANICAL ENGINEERING**
**INDIAN INSTITUTE OF TECHNOLOGY INDORE**
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# Artificial Neural Network-Based Characterization of Wrinkling Instabilities in Soft Active Materials

**A PROJECT REPORT**

*Submitted in partial fulfillment of the requirements for the award of the degrees*
***of***
**BACHELOR OF TECHNOLOGY**
**in**

**MECHANICAL ENGINEERING**

*Submitted by:*
**Khushi Kumari**
**&**
**Raja**

*Guided by:*
**Dr. Aman Khurana**



**INDIAN INSTITUTE OF TECHNOLOGY INDORE**
**DECEMBER 2025**

# CANDIDATE'S DECLARATION

We hereby declare that the project entitled **"Artificial Neural Network-Based Characterization of Wrinkling Instabilities in Soft Active Materials,"** submitted in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in ''Mechanical Engineering' completed under the supervision of **Dr. Aman Khurana,** IIT Indore, is an authentic work.

Further, we declare that we have not submitted this work for the award of any other degree elsewhere.

**Signature and name of the student(s) with date**

_____

# CERTIFICATE by BTP Guide(s)

It is certified that the above statement made by the students is correct to the best of my/our knowledge.

**Signature of BTP Guide(s) with dates and their designation**

# Preface

This report on "Artificial Neural Network-Based Characterization of Wrinkling Instabilities in Soft Active Materials" is prepared under the guidance of Dr. Aman Khurana.

It focuses on developing an ANN model to predict Breakdown voltage in dielectric elastomer membranes. The work aims to improve prediction accuracy and computational efficiency by capturing complex electromechanical behaviors that are difficult to model using traditional methods.

**Khushi Kumari**
**Raja**
B.Tech. IV Year
Discipline of Mechanical Engineering
IIT Indore

# <u>Acknowledgments</u>

# <u>Abstract</u>

This work presents an ANN framework for characterizing and predicting wrinkling instabilities in soft active materials, with particular attention to dielectric elastomer membranes. Stability in such soft material configurations is of primary concern in the design and performance of soft robotic actuators and other smart material systems. The main goal of this investigation is to improve prediction accuracy further, enhance computational efficiency, and provide a robust way of analyzing the onset of instability under various mechanical and electrical loading conditions.

Experimental measurements and numerical simulations were conducted to develop a comprehensive dataset by combining principal stretches, $\lambda_1$ and $\lambda_2$, applied voltage, and membrane thickness. These parameters constituted the input features of the ANN, whereas the corresponding wrinkling response or instability state and breakdown voltage described the outputs. This dataset represents complex nonlinear electromechanical behaviors that are challenging to model using traditional analytical methods.

Multiple ANN architectures are explored in this project, where the Feedforward ANN shows the best performance to learn the nonlinear mapping between electrical-mechanical loading and instability onset. This model predicted breakdown voltage with high accuracy while significantly reducing computational time in comparison with more traditional finite element or analytical approaches. Rigorous evaluation against experimental and theoretical results corroborates the robustness and generalizability of the approach.

Concluding, this work completes the circle between classical analytics and contemporary data-driven methodologies by integrating mechanical modeling with artificial intelligence. It envisions the possible ANN-based predictive modeling that will bring a step-change to soft robotics, smart material design, and optimization of electromechanical systems. The developed approach here illustrates well the potential of neural networks to become a key enabler of understanding and controlling such complex behaviors in soft active materials, opening up great avenues for future innovation.

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# CHAPTER1

## INTRODUCTION

### 1.1 Background

Soft active materials are a class of deformable polymeric materials whose mechanical properties can be produced by external stimuli such as electric fields, magnetic fields, light, temperature, or chemical agents. Some of the different kinds of soft active materials used include hydrogels, dielectric elastomers, shape-memory polymers, magnetically responsive soft composites, and liquid crystal elastomers. Among these various soft active materials, dielectric elastomers have emerged as one of the most promising kinds due to their high stretchability, rapid response time, low density, and the ability to endure extremely large actuation strains. These properties make DEs suitable for a wide variety of applications ranging from artificial muscles, soft robotic actuators, and stretchable sensors to adaptive optics, micro-grippers, biomimetic systems, tunable membranes, and soft wearable devices.

A dielectric elastomer actuator typically consists of a thin, compliant elastomeric membrane sandwiched between two soft electrodes. The application of voltage induces electrostatic attraction between the electrodes, compressing the membrane in the thickness direction, and expanding its surface area. This electromechanical coupling makes DE membranes function simultaneously as actuators, sensors, and energy harvesters.

### 1.2 Dielectric Elastomers and Their Electromechanical Behavior

Dielectric elastomers (DEs) are highly stretchable rubber-like materials with low elastic and moderate dielectric permittivity. When we applied Voltage, two kinds of instability were commonly observed:

    **(a) Mechanical Instabilities**
- Wrinkling instability
- Slackening
- Creasing

    **(b) Electromechanical instability**
- Pull-in instability
- Electrical breakdown

In this report, we mainly focus on wrinkling instability and electrical breakdown voltage.

## 1.3 Instability in Thin Dielectric Elastomer Membranes

**Wrinkling instability** occurs when a thin elastic membrane cannot sustain compressive stress in one in-plane direction. This happens before full breakdown, so it's a good early indicator.

Physical means of wrinkles:

> - Relieves compressive stress
>
> - Wrinkling can either precede breakdown or help delay it, depending on loading.
>
> - Wrinkles allow stable deformation without tearing

**Pull-in instability** occurs when the electrostatic attraction (Gangwar et al., 2025)between the electrodes exceeds the mechanical restoring force of the dielectric elastomer membrane.

At a critical voltage, the membrane cannot balance Maxwell **stress**, leading to:

- sudden thickness collapse,

- rapid area expansion,

- loss of force equilibrium, and

- mechanical failure unless stopped.

When voltage $V$ is applied:

1. The electric field in the membrane:

$$E = \frac{V}{t}$$

2. The Maxwell pressure (compressive electrical stress) is:

$$\sigma_{\text{Maxwell}} = \epsilon E^2 = \epsilon \left(\frac{V}{t}\right)^2$$

This pressure tries to collapse the film thickness.

Meanwhile, the stretched membrane develops mechanical restoring stress:

$$\sigma_{\text{mechanical}}$$

This mechanical stress resists the collapsing action of Maxwell stress

The membrane remains stable as long as:

$$\sigma_{\text{mechanical}} > \sigma_{\text{Maxwell}}$$

At the pull-in point, the system becomes unstable (pull-in) when:

$$\sigma_{\text{mechanical}} = \sigma_{\text{Maxwell}}$$

**Electrical breakdown voltage**: Breakdown voltage is the maximum voltage that an insulating material can tolerate before it starts to conduct electricity. This phenomenon arises from electromechanical instability (EMI), or what can be termed pull-in instability, which takes place when electrostatic forces exceed the compensating elastic forces, resulting in a sudden collapse of the membrane and often causing dielectric breakdown

## 1.4 Motivation for Using Artificial Neural Networks (ANNs)

Traditional tools such as experiments, analytical formulae, and finite-element simulations (FEM) all have their shortcomings. They are

- Time-consuming
- Sensitive to meshing
- Hard to simulate thin wrinkled regions accurately

But ANNs learn patterns from data that are limited and make quick predictions for conditions that have not been tested physically.

Although for studying deformation and wrinkling in soft materials, ANNs have been employed, rarely has the estimation of the breakdown voltage within stretched VHB membranes been tried using the same. This study introduces a compact, efficient ANN model to predict breakdown voltage for VHB films stretched equally along two directions. Using published data and carefully prepared input features, the model will learn how breakdown varies with the thickness of a film and with stretch. After training, it will have the capability to create complete 2D and 3D mapping across a wide range of both thicknesses (0.2–1.0 mm) and stretch ratios (1–3). These maps help the engineer more rapidly understand material limits and design safer soft-robotic components.

**1.5 Problem Statement**

To develop a predictive ANN model capable of estimating breakdown voltage (Dim_Vbr) in wrinkling-prone dielectric elastomer membranes (3M VHB) under varying pre-stretch ($\lambda_1, \lambda_2$) and thickness (t) conditions. The model will provide accurate forecasts and visualization tools, like 2D and 3D maps, to aid engineers in their design and experimentation.

**1.6 Objectives**

The primary objectives of this project are

- To develop an ANN model for predicting the breakdown voltage of dielectric materials.
- To preprocess and normalize experimental data for accurate ANN training.
- To identify the key parameters influencing breakdown voltage.
- To evaluate the ANN prediction accuracy using performance metrics.
- To compare ANN results with experimental/analytical values for validation.
- To create a reliable prediction framework for safer and efficient material design.

# CHAPTER2

# LITERATURE REVIEW

This work on dielectric breakdown, the influence of stretch, electromechanical failure mechanisms, and machine-learning-based prediction models in soft dielectric elastomers. It builds the scientific foundation for the ANN-based breakdown voltage prediction developed in this project.

## 2.1 Dielectric Breakdown in Soft Active Materials

Dielectric breakdown is an electrical failure characterized by a sudden increase in conduction when the applied electric field exceeds the material's dielectric strength. In soft elastomers like VHB, this occurs when:

$$E_{\text{applied}} = \frac{V_{\text{applied}}}{t} \geq E_{\text{crit}} \qquad \text{…………..(1)}$$

Because elastomers are highly stretchable, their thickness t decreases with stretch:

$$t = \frac{t_0}{\lambda_1 \lambda_2} \qquad \text{…………….(2)}$$

Thus, the electric field increases inversely with deformation. Experimental studies show:

- Breakdown voltage reduces as $\lambda_1$ and $\lambda_2$ increase
- Breakdown is highly sensitive to membrane thinning
- Mechanical stresses increase local field intensity via Maxwell stress

This directly justifies the features used in your ANN model:

$\lambda_1$, $\lambda_2$, thickness, $\lambda_2/\lambda_1$, $\lambda_1$,t — all of which control field distribution.

## 2.2 Thickness Influence on Breakdown Strength

Thicker films generally have:

- Higher breakdown voltage
- Lower probability of defect-triggered failure
- Reduced field concentration

## 2.3 Limitations of Analytical and FEM-Based Breakdown Prediction

### 1. Analytical Models

Classical breakdown models fail to incorporate:

- Large deformation
- Non-uniform fields
- Material imperfections
- Stretch-induced anisotropy

## 2. Finite Element Models

FEM can simulate thinning and field concentration, but:

- Very slow for parametric sweeps
- Sensitive to mesh density
- Difficult to simulate "true" breakdown (requires phenomenological models)

## 3. ANN Approaches for Breakdown Prediction

- ANN regression models provide highly accurate breakdown predictions
- Normalization and feature engineering improve performance
- Models generalize well if trained on representative stretch–thickness data
- Small networks  perform exceptionally well

# CHAPTER 3

# METHODOLOGY

## 3.1 Introduction

The breakdown voltage is predicted with the use of an ANN in this. An Artificial Neural Network (ANN) is basically a Feedforward Neural Network inspired by the human brain. It's useful when the relationship is complicated and nonlinear. It contains a network of neurons (or nodes) arranged in layers. Layers are the input layer, hidden layers, and the output layer, as depicted in Fig. 1. The basic structure of each neuron is similar to that depicted in Fig. 2. Weights W1 and W2 correspond to input values X1 and X2 at neuron N. A neuron takes inputs, applies weights, adds bias, and passes the result through an activation function. Here, activation functions are used to introduce nonlinearity to the network, enabling it to learn complex patterns. They are generally sigmoid, Relu (Rectified Linear Unit), Tanh, and Softmax in nature.
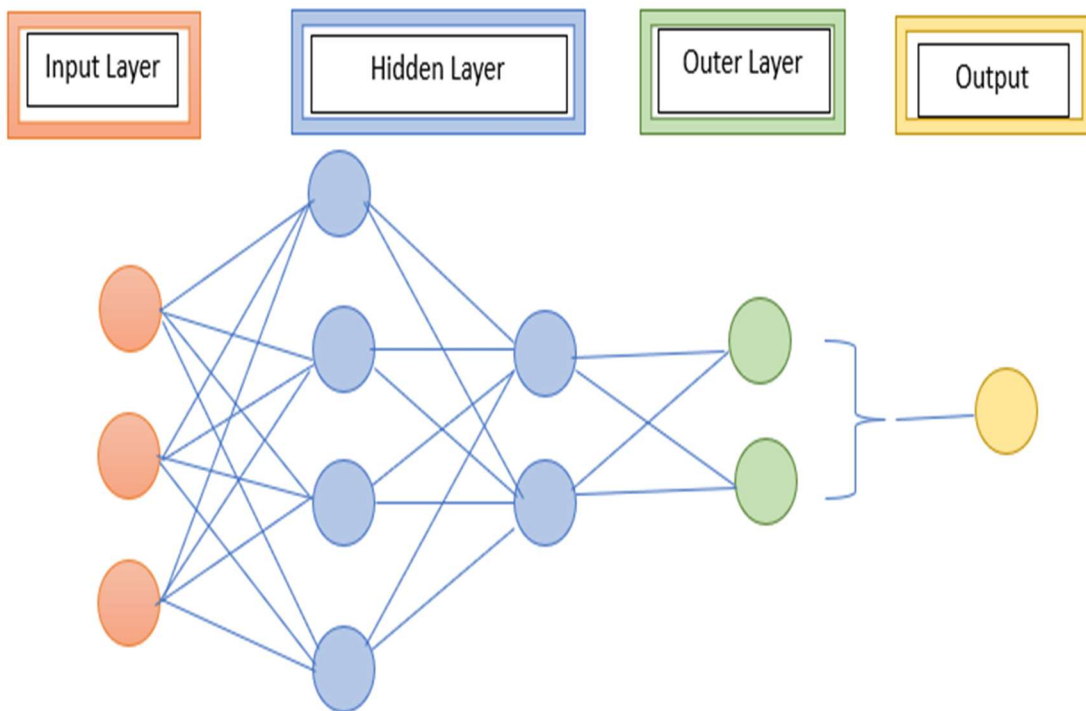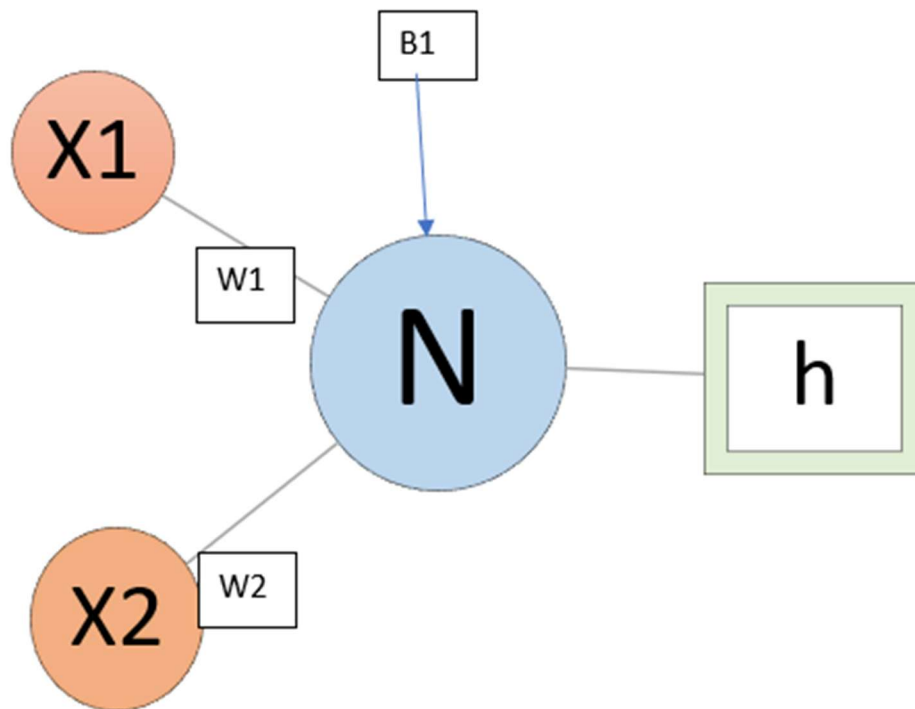


Figure 1: Artificial Neural Network: Network architecture diagram

Hidden layer and output layer calculation: Each hidden neuron computes a weighted sum of inputs + bias, then passes through an activation function (sigmoid or ReLU).

$h = W1 * X1 + W2 * X2 + B1$ ...................................(3)



output = f(h), where f is the activation function

Figure 2: Artificial Neural Network: Neuron weight distribution.

## 3.2 ANN Training using Matlab

The workflow adopted in this project closely follows the classical structure as given below.
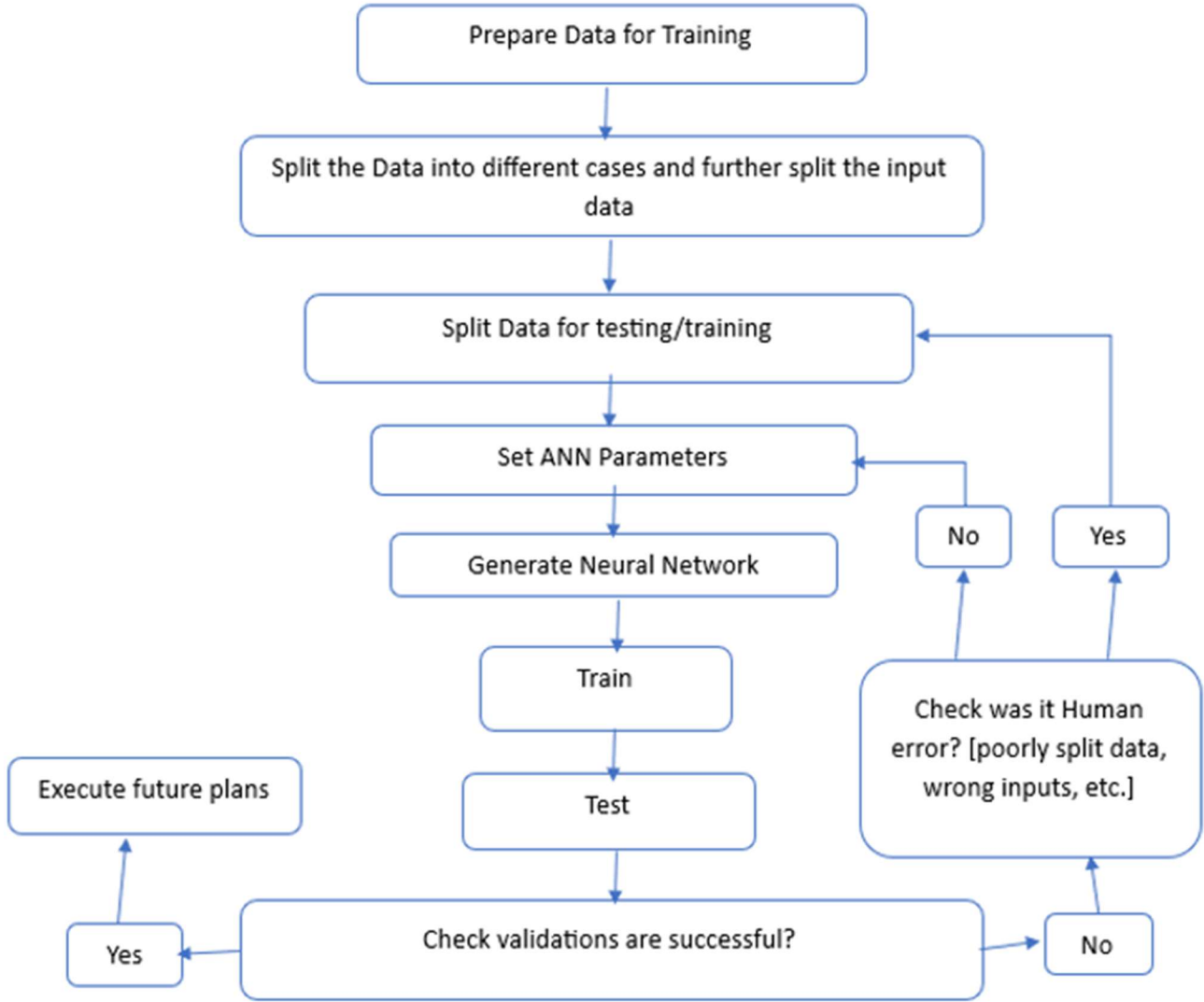


Figure 3: This is the complete structure to train a model with the help of the neural network

## Network Structure

### Step 1: Prepare Data for Training

In this work, the Input parameters are:

1. Principal stretch ratio along the x-direction ($\lambda_1$),'

2. Principal stretch ratio along the y-direction ($\lambda_2$),

3. Membrane thickness (t),

4. Aspect ratio ($\lambda_2/\lambda_1$), and

5. The interaction term ($\lambda_1 \times t$), representing effective stretched thickness.

Output parameter: Breakdown Voltage (Dim_Vbr(V))

Table 1:

| λ1 | λ2 | VHB Membrane | VHB thickness(mm) | Dim_Vbr(V) |
|----|----|----|----|----|
| 4 | 1 | 3M VHB 4905 | 0.5 | 5700 |
| 3 | 2 | 3M VBH 4905 | 0.5 | 5199 |
| 2 | 2 | 3M VHB 4905 | 0.5 | 7998 |

Table 2:

| λ1 | λ2 | VHB Membrane | VHB thickness(mm) | Dim_Vbr(V) |
|----|----|----|----|----|
| 4 | 1 | 3M VHB 5909 | 0.25 | 3081.35 |
| 4 | 1 | 3M VBH 4920 | 0.40 | 4703.80 |
| 4 | 1 | 3M VHB 4905 | 0.50 | 5750.00 |
| 4 | 1 | 3M VHB 5925 | 0.60 | 6775.34 |
| 4 | 1 | 3M VHB 4910 | 1.00 | 10729.88 |
| 3 | 2 | 3M VHB 5908 | 0.25 | 2786.08 |
| 3 | 2 | 3M VHB 4920 | 0.40 | 4253.05 |
| 3 | 2 | 3M VHB 4905 | 0.50 | 5199.00 |
| 3 | 2 | 3M VHB 5925 | 0.60 | 6126.08 |
| 3 | 2 | 3M VHB 4910 | 1.00 | 9701.68 |
| 2 | 2 | 3M VHB 5908 | 0.25 | 4286.78 |
| 2 | 2 | 3M VHB 4920 | 0.40 | 6542.78 |
| 2 | 2 | 3M VHB 4905 | 0.50 | 7998.00 |
| 2 | 2 | 3M VHB 5925 | 0.60 | 9424.20 |
| 2 | 2 | 3M VHB 4910 | 1.00 | 14924.80 |

The dataset compiled for training and validation of the ANN corresponding to the Wrinkling Instabilities and breakdown voltage in Soft Active Materials has been summarized in Tables 1 and 2 as reported in [1],[2]

**Step 2: Split the Data Into Cases**
Divide the experimental dataset into:
- Case-1: Varying $\lambda_1$
- Case-2: Varying $\lambda_2$
- Case-3: Varying thickness
- Case-4: Combined conditions

**Step3: Split Data Into Training & Testing Sets**

- For Training: 70%

- For Testing and Validation: 30%

**Step 4: Set ANN Parameters**

- ANN Type: Feed-forward backpropagation
- Hidden Layers:
  - Layer 1: 64 neurons
  - Layer 2: 32 neurons

- Activation function: ReLU activation
- Output Layer: 1 neuron (linear activation)
- Optimizer: Adam
- Learning Rate: 0.001
- Batch Size: 16
- Maximum Epochs: 100

We use the Adam optimizer due to its robustness in handling moderate data sizes and its ability to converge efficiently without extensive hyperparameter tuning.

We tested sigmoid, tanh, and ReLU. ReLU performed best because it avoids vanishing gradient problems common in deeper networks and provides faster convergence for our dataset size. It also handles the positive nature of our output parameters well.

**Step 5: Generate the Neural Network, then train and test the model by putting different values in the model.**

**Step 6: Check if Validation is Successful**

The parameters were adjusted and tested repeatedly until the loss decreased and the model began to produce consistent results. To make sure it wasn't overfitting, compared its accuracy on training and test data, and also checked the prediction errors.

To check model accuracy, we applied three measures that determine the model performance-

1. **Root Mean Square Error (RMSE)**

$$RMSE = \sqrt{\frac{1}{N}\sum(y - \hat{y})^2} \qquad \ldots\ldots\ldots\ldots..(4)$$

2. **Mean Absolute Error (MAE)**

$$MAE = \frac{1}{N}\sum |y - \hat{y}| \qquad \ldots\ldots\ldots\ldots\ldots(5)$$

3. **Coefficient of Determination (R²)**

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \qquad \ldots\ldots\ldots\ldots..(6)$$

Where:

- $SS_{res}$= residual sum of squares
- $SS_{tot}$= total variance
- R² near 1, excellent prediction

  R² = 0, average

  R² < 0, poor prediction

The input features chosen correctly represented the behavior of dielectric breakdown under biaxial pre-stretch. We saved the trained model and all scale values for future use. A small MATLAB program was also made for quick predictions. It loads the saved model, asks for $\lambda_1$, $\lambda_2$, and thickness, processes the input automatically, and then shows the predicted breakdown voltage onscreen.

**Step 7: After following all steps, save the model**

# ChApter4

# Breakdown Voltage Prediction Model

**4. 1.  Model Code**

**4. 1.1 This is a training model------------------**

```matlab
% vhb_breakdown_ann_simple.m
% Simple ANN script
% Assumes no missing values and numeric columns are present.

clear; clc; close all;
filePath = "VHB_breakdown_dataset.xlsx";
if ~isfile(filePath)
error("File not found: %s", filePath);
end
T = readtable(filePath,'PreserveVariableNames',true);

% Column names (change if needed)
col_lambda1 = "λ1";
col_lambda2 = "λ2";
col_thickness = "VHB Membrane";
col_vbr = "Dim_Vbr (V)";

% Directly use numeric columns (assumes already numeric)
lambda1 = T{ :, col_lambda1};
lambda2 = T{ : ,col_lambda2};
thickness = T{ : ,col_thickness};
Vbr = T { : ,col_vbr};

% --- Minimal feature engineering ---
aspect = lambda2 ./ lambda1;       % λ2/λ1
```

```matlab
l1t   = lambda1 .* thickness;      % interaction
X = [lambda1, lambda2, thickness, aspect, l1t];
Y = Vbr(:);


% Simple split: 70% train, 30% test
N = size(X,1);
idx = randperm(N);
nTrain = round(0.7 * N);
trainIdx = idx(1:nTrain);
testIdx  = idx(nTrain+1:end);
Xtrain = X(trainIdx, :);
Ytrain = Y(trainIdx);
Xtest = X(testIdx, :);
Ytest = Y(testIdx);


% Standardize using train statistics
muX = mean(Xtrain,1);
sigmaX = std(Xtrain,[ ],1);
sigmaX(sigmaX==0) = 1;
XtrainZ = (Xtrain - muX)/ sigmaX;
XtestZ  = (Xtest - muX) ./ sigmaX;
muY = mean(Ytrain); sigmaY = std(Ytrain);
YtrainZ = (Ytrain - muY) ./ sigmaY;


% --- Simple ANN ---
layers = [
featureInputLayer(size(XtrainZ,2), 'Normalization', 'none')
fullyConnectedLayer(64)
reluLayer
fullyConnectedLayer(32)
reluLayer
```

```matlab
fullyConnectedLayer(1)
regressionLayer
];

opts = trainingOptions('adam', ...
'InitialLearnRate',1e-3, ...
'MaxEpochs',100, ...
'MiniBatchSize',16, ...
'Shuffle', 'every-epoch', ...
'Verbose', false);
fprintf('Training simple ANN...\n');
net = trainNetwork(XtrainZ, YtrainZ, layers, opts);

% Predict and evaluate
YpredZ = predict(net, XtestZ);
Ypred = YpredZ * sigmaY + muY;

res = Ytest - Ypred;
RMSE = sqrt(mean(res.^2));
MAE = mean(abs(res));
SS_res = sum(res.^2);
SS_tot = sum((Ytest - mean(Ytest)).^2);
R2 = 1 - SS_res/SS_tot;

fprintf('\nResults on test set:\nRMSE = %.4f\nMAE = %.4f\nR^2 = %.4f\n', RMSE, MAE, R2);

% Plot
figure; scatter(Ytest, Ypred, 50, 'filled'); hold on;
mn = min([Ytest; Ypred]); mx = max([Ytest; Ypred]);
plot([mn mx],[mn mx],'k--'); xlabel('True Dim\_Vbr (V)'); ylabel('Predicted Dim\_Vbr (V)');
```

title(sprintf('ANN: R^2=%.3f, RMSE=%.3f', R2, RMSE)); grid on; axis equal;

% Save model and scalers

save('vhb_ann_simple.mat', 'net', 'muX', 'sigmaX', 'muY', 'sigmaY');

fprintf('Saved ANN model to vhb_ann_simple.mat\n');

**4. 1.2 This is a testing model: Predicting breakdown voltage at any λ₁, λ₂, thickness------------------**

% --- Interactive prediction using saved ANN model ---

load('modal_for_breakdown_voltage.mat', 'net', 'muX', 'sigmaX', 'muY', 'sigmaY');

% Ask user for input

new_lambda1   = input('Enter λ1: ');

new_lambda2   = input('Enter λ2: ');

new_thickness = input('Enter VHB Membrane thickness: ');

% Feature engineering (same as training)

new_aspect = new_lambda2 / new_lambda1;

new_l1t    = new_lambda1 * new_thickness;

Xnew = [new_lambda1, new_lambda2, new_thickness, new_aspect, new_l1t];

% Standardize using training stats

XnewZ = (Xnew - muX)/ sigmaX;

% Predict (normalized output)

YnewZ = predict(net, XnewZ);

% Rescale to original units
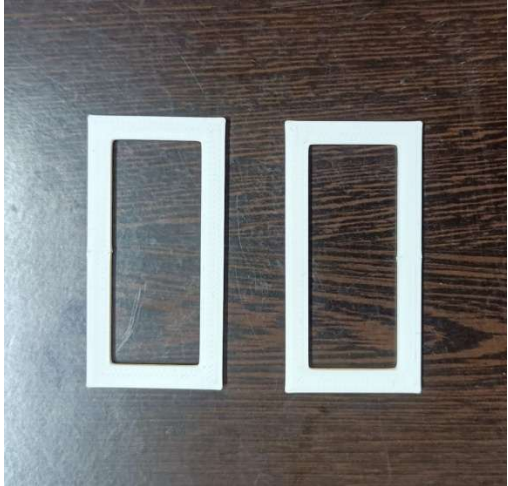
Ynew = YnewZ * sigmaY + muY;
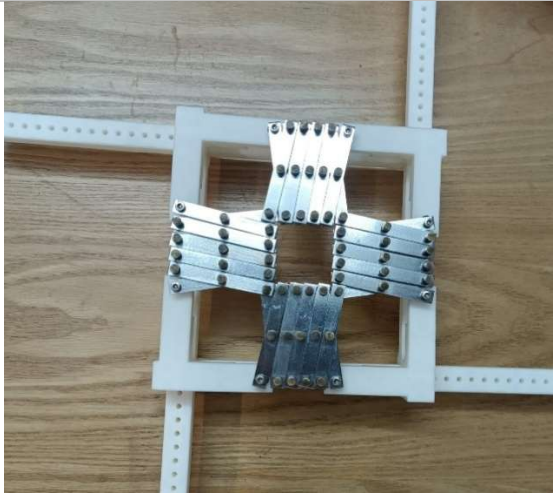
fprintf('Predicted Dim_Vbr (V) = %.4f\n', Ynew);

# CHAPTER5
# EXPERIMENT

## 5.1 Experiment setup:

| Requirement | Purpose | setup |
|---|---|---|
| 3M VHB Tape | It is a Dielectric elastomer membrane used for experimentation. |  |
| PLA (Polylactic acid) or PET (polyethylene terephthalate) | To make a rigid frame (3D), which is essential for pre-stretching and holding the VHB membrane in a uniform and controlled manner. |  |

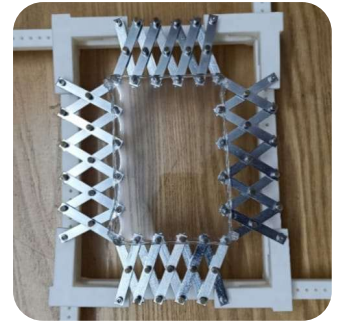| | | |
|---|---|---|
| Stretching mechanisms | Use to pre-stretch VHB for 24 hours. |  |
| Power supply source | To supply a DC voltage |  |
| Copper strips | To pass current to the membrane |  |

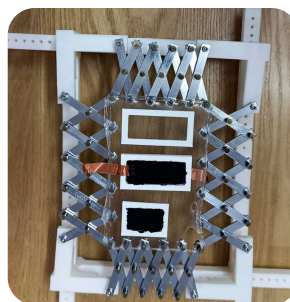## 5.2 Experiment Procedure and Results:



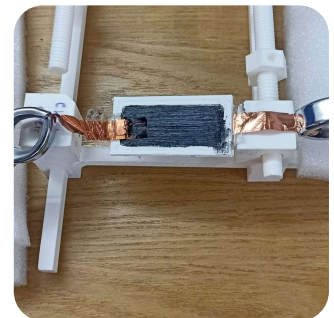Take 3M VHB
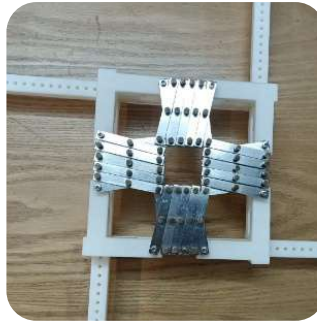


Apply it to the stretching mechanism



pre-stretch it for 24 hours

direction λ1 in X1

λ2 in x2 (3x2)



add frame
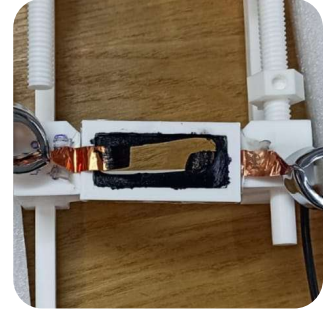


apply carbon grease and copper strips



supply voltage

formation of wrinkling pattern will start to appear when the voltage reaches to critical voltage

breakdown voltage

Failure of material (3M VHB 4910)

# RESULTS AND DISCUSSION

## 6.1 Breakdown Voltage vs Thickness (2D Line Plots)

Presents the ANN-predicted variation of breakdown voltage with membrane thickness for two different stretch conditions:

i.      $\lambda_1 = 4.0, \lambda_2 = 1.0$

ii.     $\lambda_1 = 2.0, \lambda_2 = 2.0$

In both cases, the breakdown voltage shows a consistent and increasing trend as the membrane thickness increases. This is expected because a thicker dielectric layer provides greater resistance to electrical failure, allowing higher voltages to be sustained before breakdown occurs.

When comparing the two stretch conditions, the Equi-biaxial case ($\lambda_1 = \lambda_2 = 2.0$) exhibits higher voltage capacity for the same thickness than the non-uniform stretch ($\lambda_1 = 4.0, \lambda_2 = 1.0$). This suggests that membranes under more balanced stretching distribute stresses more evenly and therefore show improved electrical stability. The ANN model successfully reproduces this physically realistic trend, confirming that membrane thickness is a dominant factor influencing breakdown voltage.
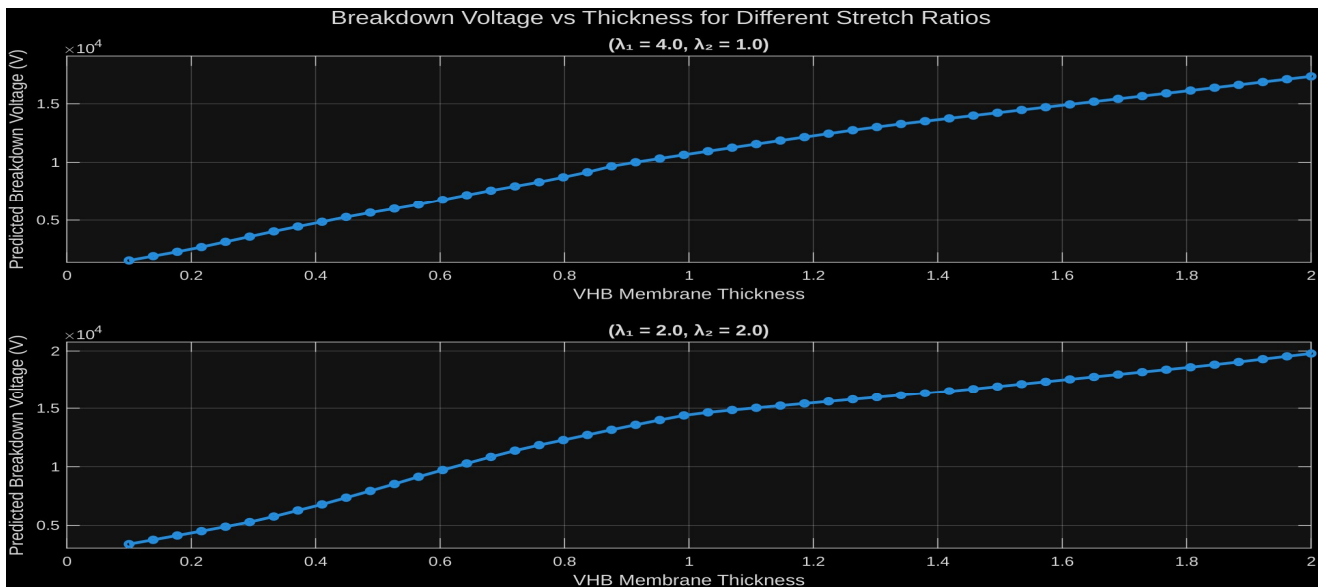


Figure 4: Breakdown Voltage vs. Thickness (2D Line Plots)

## 6.2 Effect of Stretch Ratios on Breakdown Voltage (2D Contour Plots)

This graph shows the variation of predicted breakdown voltage as a function of the stretch ratios $\lambda_1$ and $\lambda_2$ for two different membrane thicknesses.

For the thinner membrane, the contour map shows strong variations in voltage over the stretch domain. Small changes in $\lambda_1$ and $\lambda_2$ lead to noticeable changes in breakdown voltage. This indicates that thin membranes are susceptible to stretching and are more prone to instability.

In contrast, the contour plot corresponding to the thicker membrane displays a smoother distribution and generally higher voltage levels. Although the breakdown voltage still decreases with increasing overall stretch, the change is more gradual. This means that thicker membranes maintain performance over a wider range of deformations.

These observations indicate that increasing thickness improves the resistance of the elastomer to stretch-induced electrical failure.
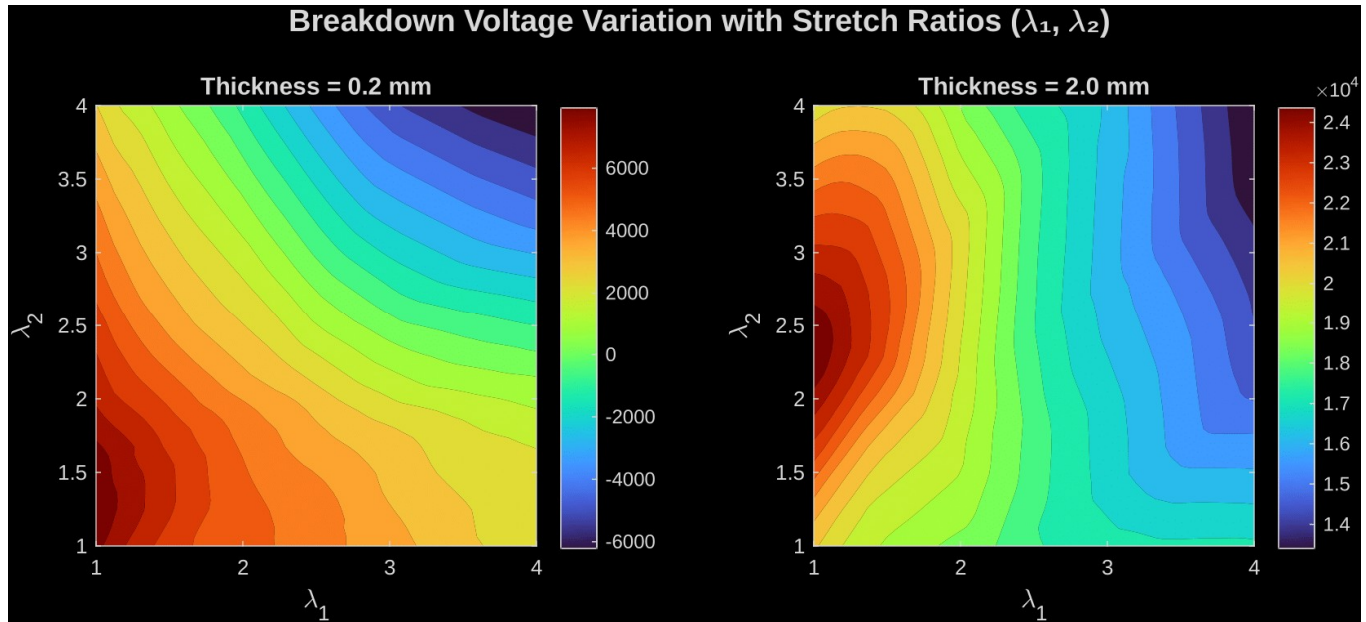


Figure 5: Breakdown Voltage vs. Stretch Ratios (2D Contours)

## 6.3 3D Surface Representation of Breakdown Voltage

This figure shows a three-dimensional surface plot of the ANN-predicted breakdown voltage as a function of the two stretch ratios for several thickness values.

Each surface represents a different membrane thickness. For any fixed pair of stretch ratios ($\lambda_1$, $\lambda_2$), the predicted voltage increases as the thickness increases. This confirms that the membrane thickness has a direct and positive influence on the breakdown voltage.

The surface is not flat, which indicates a nonlinear interaction between the stretch ratios and the voltage response. At higher stretch values, the voltage tends to decrease due to reduced effective thickness and the onset of electromechanical instability.

This plot provides a clear visual understanding of how breakdown voltage depends simultaneously on deformation and thickness, demonstrating the ability of the ANN to capture complex, nonlinear behavior.
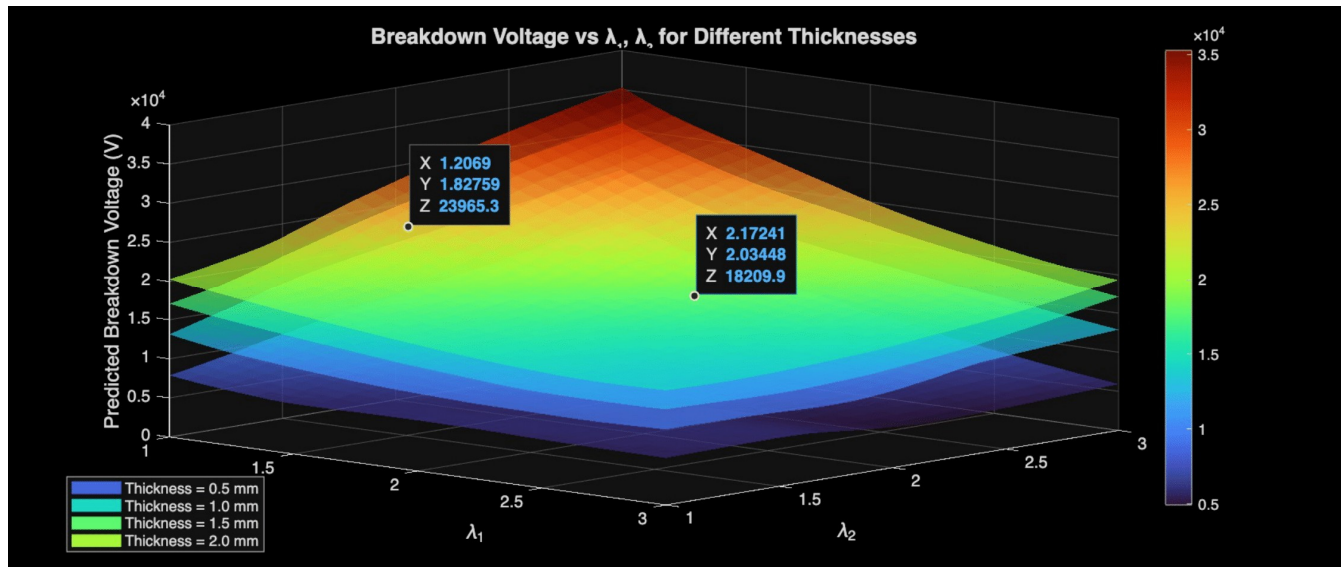


Figure 6: 3D Surface Plot (Predicted Voltage)

## 6.4 3D Combined Breakdown Voltage

This 3D graph plots the "Breakdown Voltage" (Z-axis) as a function of the two stretch ratios, $\lambda_1$ (x-axis) and $\lambda_2$ (y-axis). It features four stacked, semi-transparent surfaces, each representing a different membrane thickness: 0.2 mm, 0.8 mm, 1.4 mm, and 2.0mm. Similar to the previous 3D plot, this figure effectively illustrates that the voltage capacity increases with thickness for any given pair of stretch ratios. The surfaces show a general trend of decreasing voltage as the stretch ratios increase.
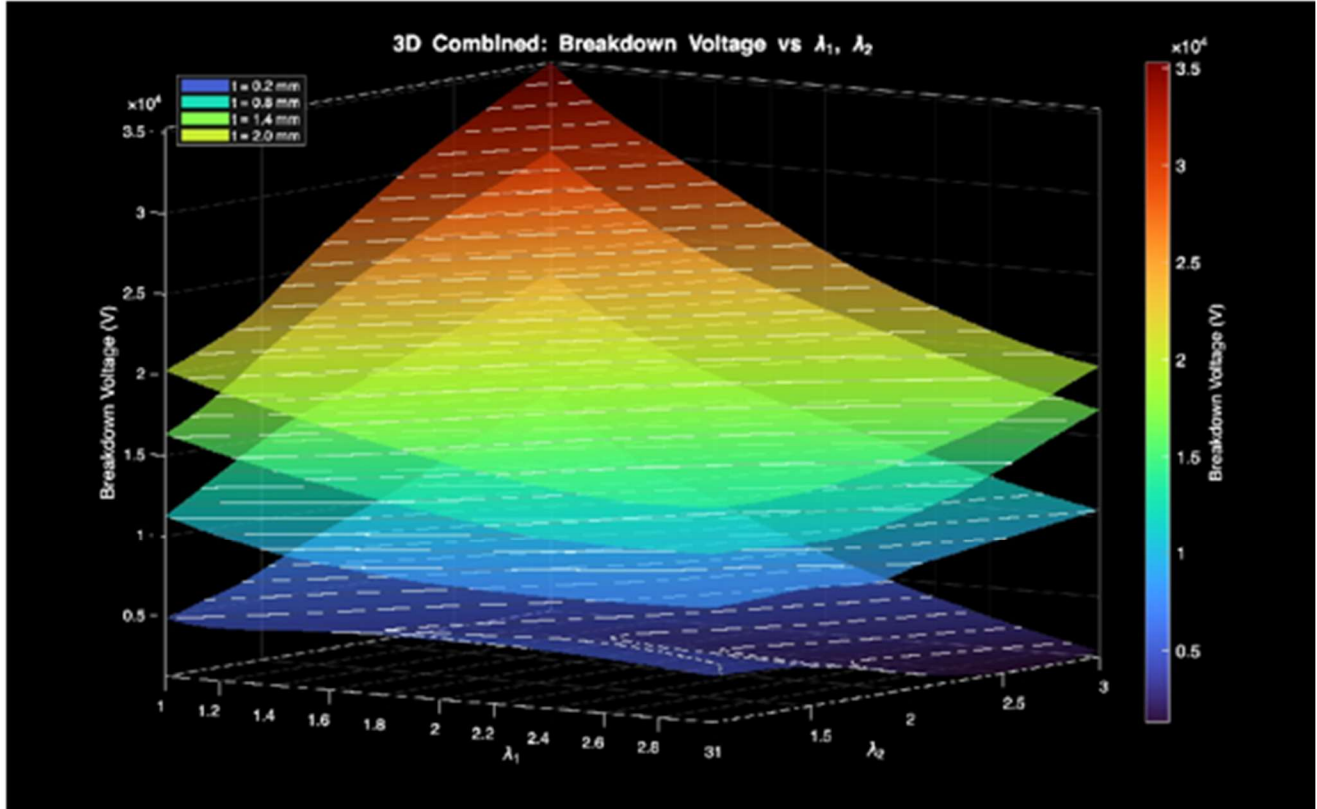


Figure 7: 3D Combined Breakdown Voltage

## 6.5 Filled Contour Plots for Individual Thicknesses

This provides filled contour maps of breakdown voltage for selected thickness values. Each plot offers a top-view representation of the voltage distribution in the $\lambda_1$-$\lambda_2$ plane.

For the smallest thickness, high-voltage regions are limited to a narrow range of stretch values, indicating restricted safe operating conditions. As the thickness increases, the area corresponding to higher breakdown voltage expands significantly.

This means that thicker membranes not only tolerate higher voltages but also remain stable over a broader range of deformation. These plots are extremely useful for selecting appropriate thickness values in soft actuator design.
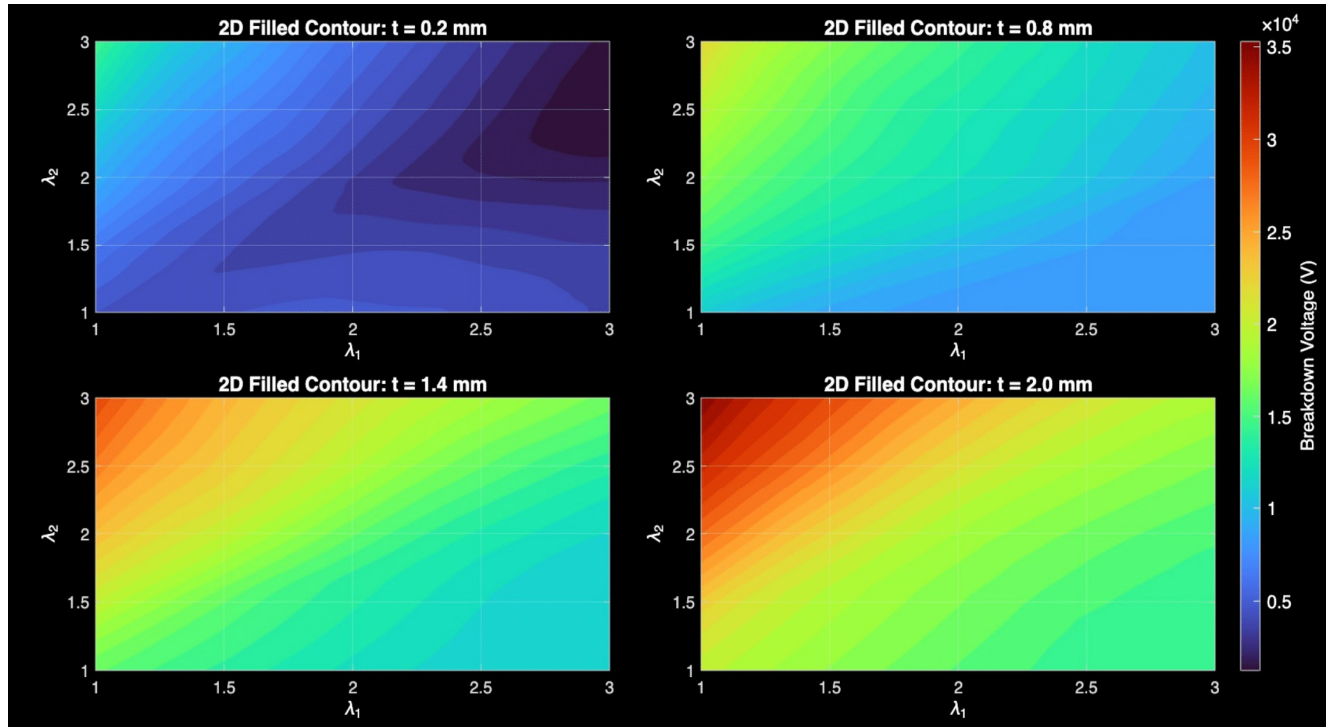


Figure 8: 2D Filled Contours (by Thickness)

## 6.6 2D Contour Overlay for Thickness Comparison

This combines contour lines for all thickness values into a single plot. Each contour represents a constant breakdown of voltage for a specific membrane thickness. As the thickness increases, the contours shift outward in the $\lambda_1$-$\lambda_2$ space. This indicates that higher voltage levels can be achieved at larger stretches when the membrane is thicker.

Even relatively small increases in thickness lead to noticeable improvements in breakdown resistance. This comparison further supports the conclusion that thickness is a highly influential design parameter. The consistent and systematic movement of contour lines also confirms the reliability and smooth generalization capability of the trained ANN model.
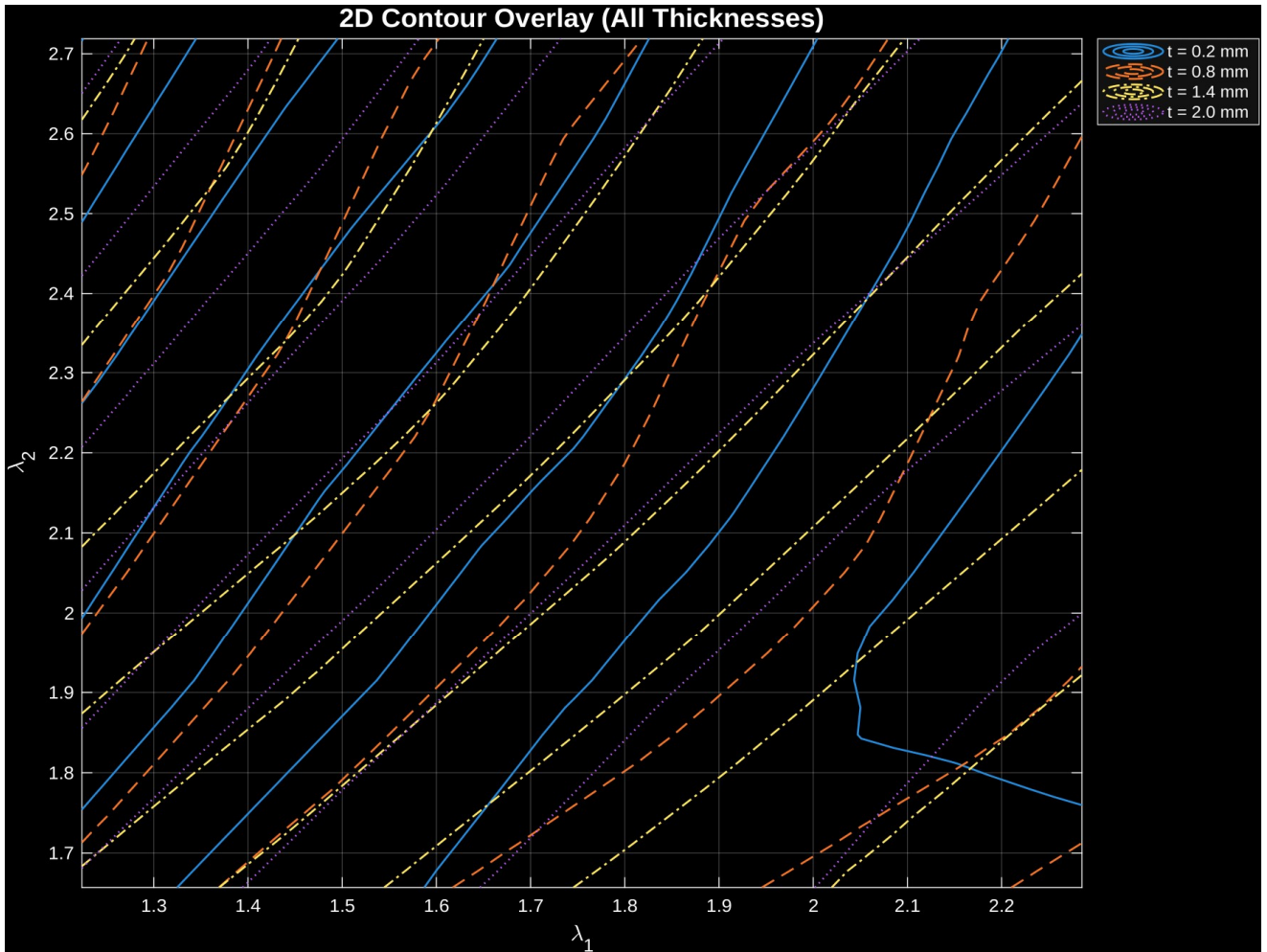


Figure 9: 2D Contour Overlay for Thickness Comparison

# EXPERIMENTAL VS MODEL RESULTS

**(a). Predicted vs True Breakdown Voltage**

The scatter plot shows a strong, high prediction accuracy with only minor acceptable deviations. This confirms that the ANN generalizes well and reliably captures the nonlinear behavior of dielectric elastomers.
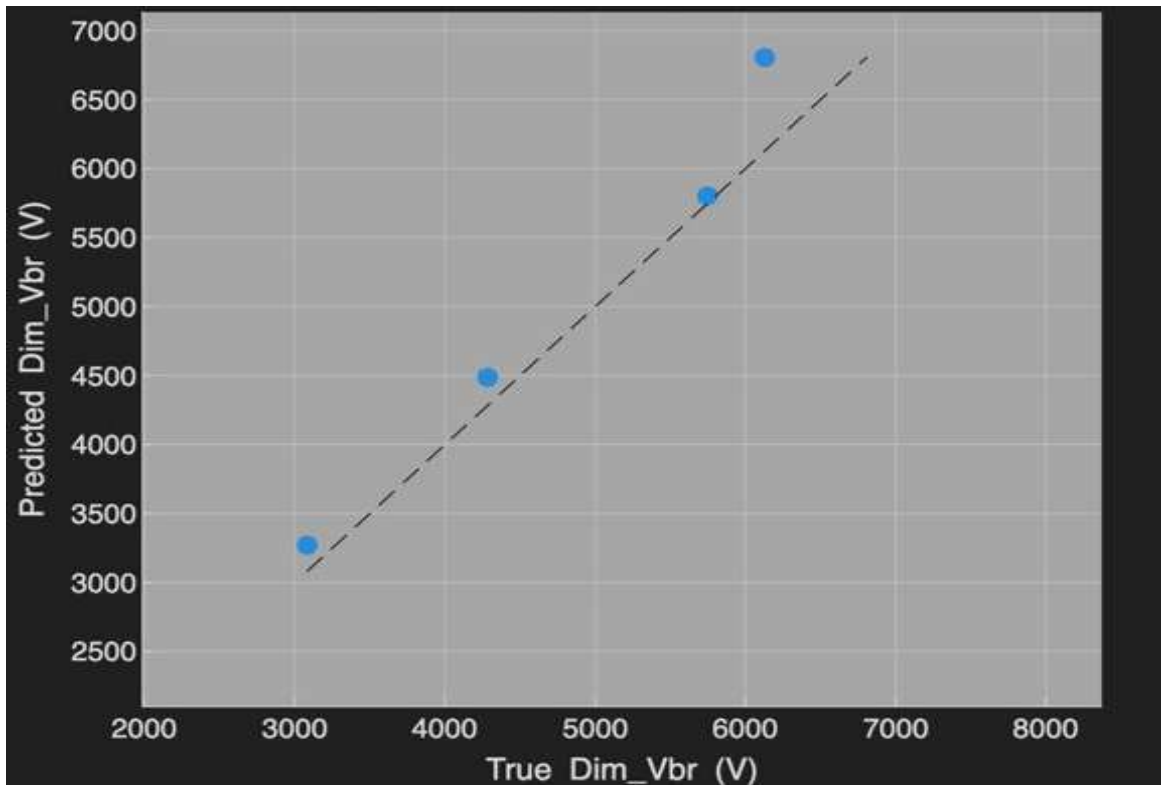


Figure 10: graph b/w predicted breakdown voltage v/s True Breakdown Voltage

**(b). Performance Analysis (t = 1 mm)**

The second plot compares experimental and ANN-predicted breakdown voltages for the following stretch configurations: $(\lambda_1, \lambda_2)$: (1,4), (2,2), (2,3), (1,2), (1,3)

Across all cases, the ANN closely follows the experimental trend and captures variations in breakdown voltage with changing stretch states. Small differences arise due to experimental uncertainties, but overall, the model provides smooth and consistent predictions suitable for design and analysis.
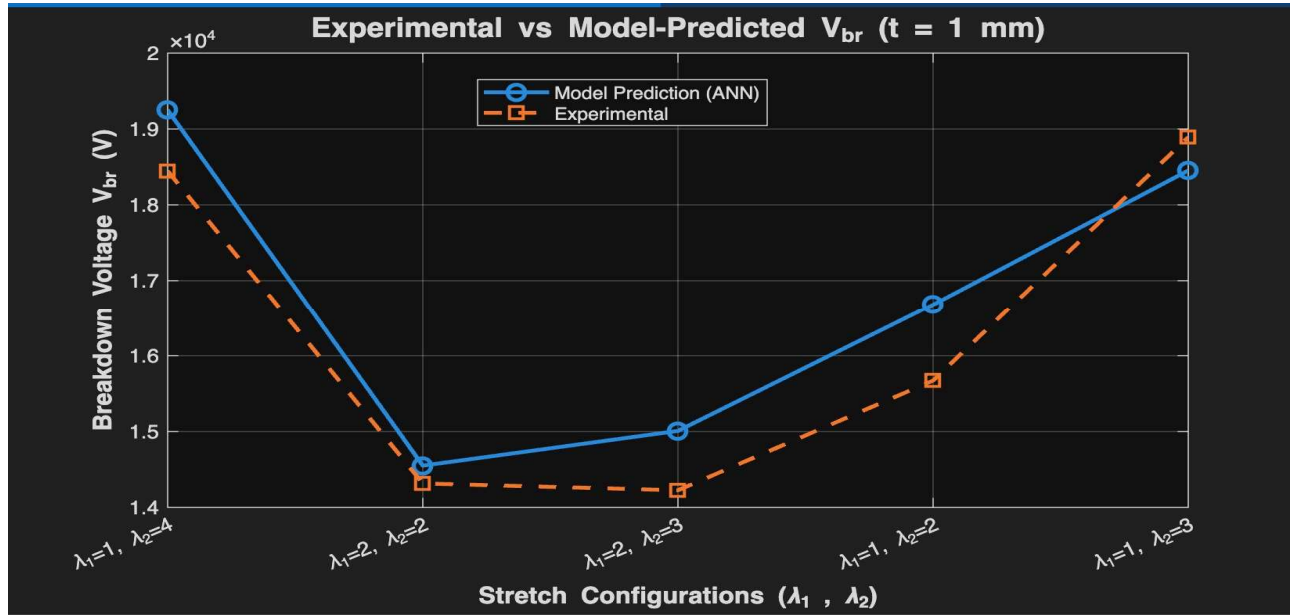


Figure 11: Performance Analysis b/w Experiment and ANN Model

# CHAPTER 7
# CONCLUSION AND FUTURE SCOPE

This study presents an artificial neural network (ANN)-based model designed to predict the breakdown voltage of pre-stretched VHB membranes as a function of principal stretch ratios and membrane thickness. By integrating physics-informed feature engineering with a compact feedforward neural architecture, the model demonstrates robust predictive capabilities in capturing the nonlinear relationship between breakdown voltage and both stretch and thickness.

Notably, the ANN successfully reproduces trends established through experimental and numerical methods: the rise-and-fall behavior of breakdown voltage (Vbr) concerning stretch, as well as the monotonic increase of Vbr with membrane thickness. The model's ability to generate high-resolution parametric maps within seconds highlights the significant computational efficiency that ANN surrogates can offer compared to exhaustive experimental or finite element method (FEM) studies.

This efficiency will prove particularly beneficial in the design workflow for soft actuators and dielectric elastomers, where extensive parameter sweeps are necessary to identify optimal configurations. The trained ANN model can serve as a rapid screening tool to evaluate designs before committing to costly laboratory and computational tests.

Future work could build upon this foundation by including additional parameters such as loading rate, preconditioning cycles, electrode type, and temperature; training on larger experimental datasets to enhance generalization; developing uncertainty-aware ANN models; and integrating the ANN surrogate into real-time control and adaptive voltage-limiting schemes for soft actuators.

# REFERENCE

1) 2022Aman Khurana, Giuseppe Zurlo, and M. M. Joglekar. "Electromechanical stability of wrinkled dielectric elastomers" International Journal of Solids and Structures, 246, 111613. [Impact Factor: 3.8].

2) Arpit Kumar Srivastava and Sumit Basu "Mechanics of reversible wrinkling in a soft dielectric elastomer DOI: 10.1103/PhysRevE.101.040501

3) Gangwar, A. S., Khurana, A., & Sharma, A. K. (2025). Wrinkling stability in soft dielectric elastomers: The role of strain stiffening and stretch-dependent permittivity. *International Journal of Solids and Structures*, *318*, 113429. https://doi.org/10.1016/j.ijsolstr.2025.113429

4) Aman Khurana, Asesh Kumar Patra & M. M. Joglekar (2023) An energy-based model of dielectric elastomer minimum energy structures with stiffeners: Equilibrium configuration and the electromechanical response, Mechanics of Advanced Materials and Structures, 30:13, 2574-2592, DOI: 10.1080/15376494.2022.2059599.

5) Godaba, H., Zhang, Z.-Q., Gupta, U., Foo, C. C., & Zhu, J. (2019). Instabilities in dielectric elastomers: buckling, wrinkling, and crumpling. Soft Matter.

6) Sankalp Gour, Deepak Kumar, Aman Khurana, Unequal-biaxial taut states of functionally graded dielectric elastomers, International Journal of Engineering Science,214 (2025) 104291.