# WBS3 – 방열소재 CT이미지 분석을 통한 물성(열전도도, 내전압) 예측 S/W 개발

진행상황보고

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# Project Goal

The main goal of the project is to predict the values of Physical Properties (such as thermal conductivity, withstand voltage and viscosity) for thermal Insulation materials from their CT scans with the assistance of AI.

- Thermal conductivity
  *Defined as:* the rate at which heat passes through a specified material, expressed as the amount of heat that flows per unit time through a unit area with a temperature gradient of one degree per unit distance.
- Withstand voltage
  *Defined as:* Indicates the amount of voltage that can be resisted when applied for three minutes in still air at 25 ˚C. Withstand voltage is measured using a method that starts at 0V and then gradually increases the amount of voltage applied.

# Introduction

# Introduction – Material

- Thermal insulating materials is the general name for thermal preserving and heat insulating materials widely used in the automotive industry.
- The materials are made up of aluminium oxide $Al_2O_3$ and Silicon dioxide $SiO_2$ with an 50:50 volumetric and 80:20 Wt. Percentage respectively.
- The materials are made by using the process of sintering, which is a heat treatment process where loose material (Aluminium oxide) is subjected to high temperature and pressure in order to compact it into a solid piece.
- Inhomogeneous shrinkage is caused by sintering drive force.

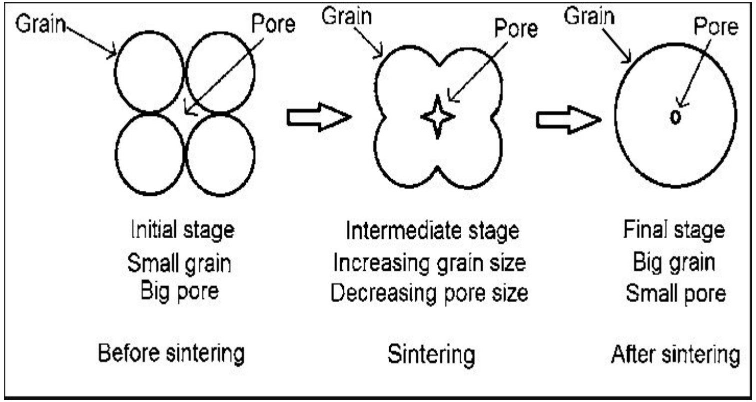



*Figure 1: Making Process of Materials*

# Introduction – Elements

- Filler/Grain
- Cavities/pores
- Binder
- Holes

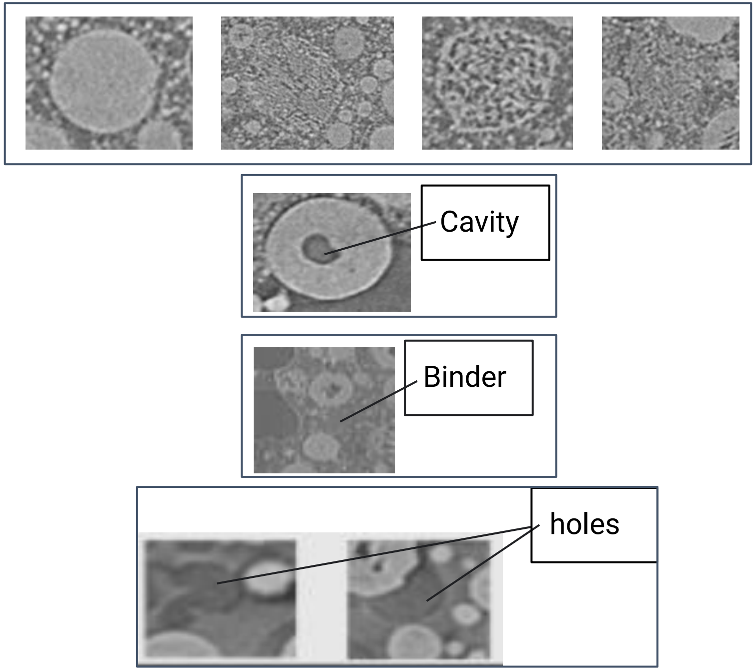



*Figure 2: Elements of the materials*

# Introduction – Filler Classification

- Fillers are then divided into 3 subcategories based on their size:
  - Small (5~70 micrometre)
  - Medium (70~120 micrometre)
  - Big (120~120+ micrometre)
- The categories are based on the actual size of filler ($Al_2O_3$) particles as 5, 70 and 120 micrometre diameter particles were used in the manufacturing process of these materials.

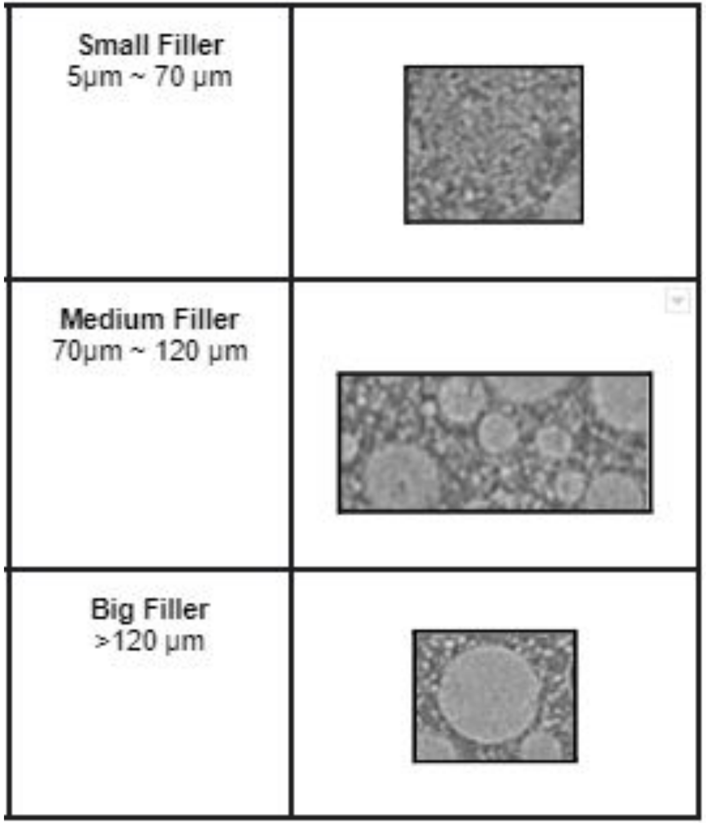



*Figure 3: Classification of Fillers*

# Literature Review

# Literature Review

Detailed Literature Review

**Insights:**

A detailed literature review provided the following insights about the thermal insulation materials:

- Aluminium oxide filler is added to silicon resin binder to increase the thermal conductivity of the material.
- No obvious voids between the filler particles (cavities) and silicone resins (holes) enhance the thermal conductivity of the composites.
- Small particles easily occupy the spaces that the large particles cannot occupy, thus forming a very effective thermally conductive pathway.
- Sintering after a certain limit decreases thermal conductivity, which indicates that presence of more big fillers affect thermal conductivity
- Effective thermally conductive pathways improve thermal conductivity.
- Breakdown voltage is affected by Filler content
- Viscosity is affected by Filler content as increase in $Al_2O_3$ causes increase in viscosity

**Possible Features:**

The above mentioned observations from literature were used to list down possible features that can be used for the development of AI. The possible features are listed below as:

- Ratios of all elements in the whole material (ratio of fillers, binder, holes and cavities in the whole material)
- Ratio of each element relative to the rest of the elements such as ratio of filler to binder, ratio of cavities to filler etc.
- Ratio of small, mid and big fillers in the whole material
- Standard deviation of all elements.
- Ratios of each filler type to the rest of the elements such as ratio of small fillers to all fillers, ratio of big fillers to cavities etc.
- Density heat maps of all elements and filler types
- Mean Nearest Neighbour Distance for all elements and filler types
- Effective thermally conductive pathways/ Heat Transfer pathways (HTPs)

# Feasibility Analysis

# Feasibility Analysis – Phase 1

Link to detailed document

healthhub

**Phase 1: Feature Extraction**

HMotors provided scans from two different companies i.e. Ceramic company scans (3W) and Ceramic company scans (5W) and the goal was to extract as many as possible visible elements from the scans.

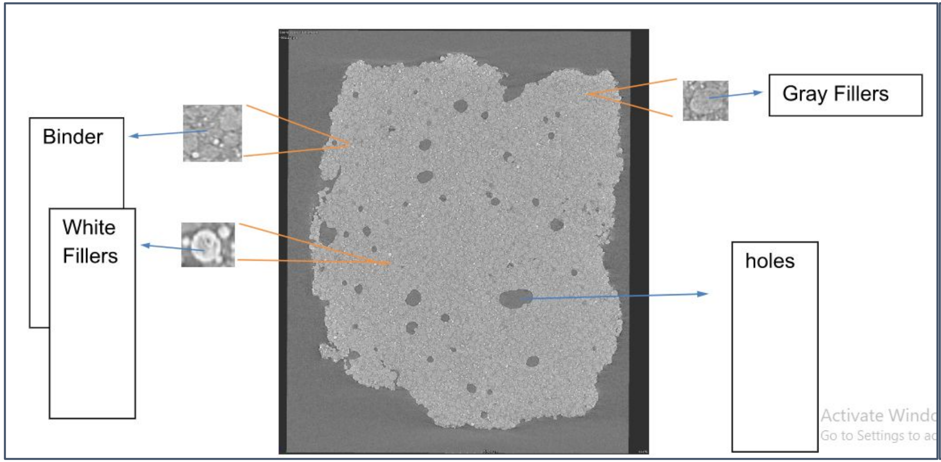



*Figure 4: Ceramic Company Scan (3W)*

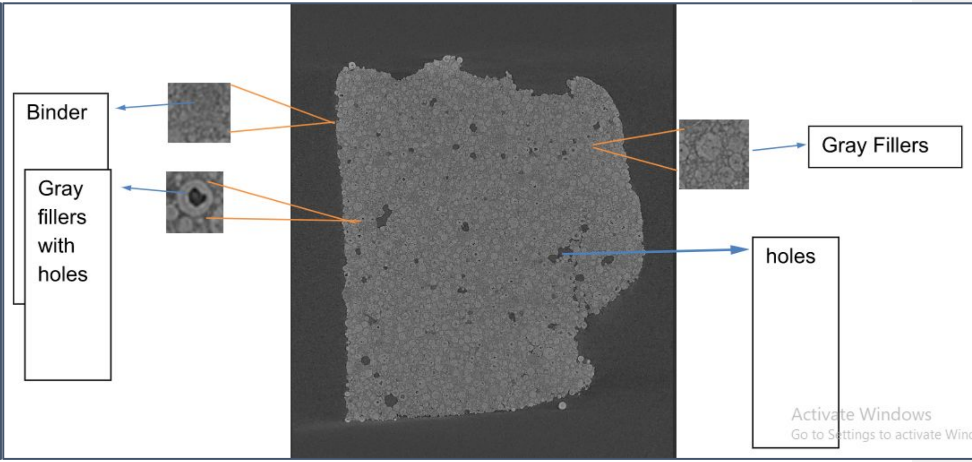



*Figure 5: Ceramic Company Scan (5W)*

The scans were provided in vgl file format. After our analysis we **concluded** that the scans had a high resolution which made extraction of all the labelled elements possible but we faced some limitations in fully automating the feature extraction task because of the file format. Therefore, we **recommended** providing similar quality scans in DICOM file format.

# Feasibility Analysis – Phase 2

**Phase 2: Company Analysis**

In phase 2, we were given five different scans which were from different scanning companies as listed below:

- Internal Company
- 히오트 (External Company 1)
- 세라믹기술원(External Company 2)
- 기초과학공동기기원 (External Company 3) Data 1
- 기초과학공동기기원 (External Company 3) Data 2

Based on our initial analysis, it was **recommended** to use Data 2 from 기초과학공동기기원 (External Company 3) as it provided all the required information and had better resolution compared to the rest

Link to detailed document

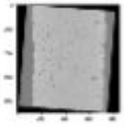
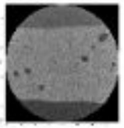
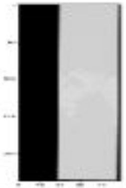
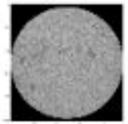
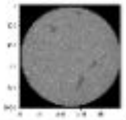
| Samples | Available Features | | | | | Original Sample |
|---|---|---|---|---|---|---|
| | Holes | Filler Type 1 | Filler Type 2 | Fillers with Cavity | Fillers without Cavity | |
| Internal Company Samples | ✓ | × | ✓ | ✓ | ✓ |  |
| External Company 1 히오트 | ✓ | ✓ | ✓ | × | ✓ |  |
| External Company 2 세라믹기술원 | ✓ | ✓ | ✓ | × | ✓ |  |
| External Company 3 Data 1 기초과학공동기기원 | ✓ | × | ✓ | ✓ | ✓ |  |
| External Company 3 Data 2 기초과학공동기기원 | ✓ | ✓ | ✓ | × | ✓ |  |

*Figure 6: Comparison of data samples*

# Feasibility Analysis – Phase 3

Link to detailed document

### Phase 3: Shooting Conditions/views

The next goal was to analyse and compare 3 different views of the material to decide the scanning conditions for future work.

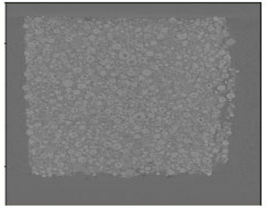
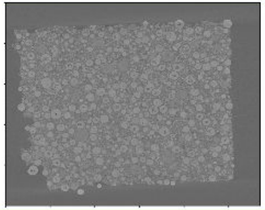
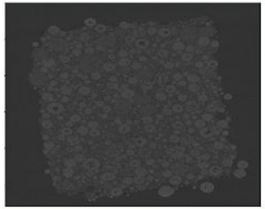
| View | Big | Mid | Small |
|---|---|---|---|
| Dimensions | 2478x2085 | 2500x2856 | 2800x2535 |
| Pixel Spacing (µm) | 1.799\1.799 | 1.200\1.200 | 0.950\0.950 |
| Total no. of Slices | 1221 | 1879 | 1105 |
| No. of slices containing material | 969 | 1493 | 699 |
| Depth of material covered = No. of slices containing material * pixel spacing (µm) | 969*1.799 = 1743.231 | 1493*1.2 = 1791.6 | 699*0.95 = 664.05 |
| Sample scan images |  |  |  |

*Figure 7: Specifications of provided views*

Based on our analysis, we **recommended** to use small view for future work as small view had better resolution and less pixel spacing hence the scans gave better extraction of elements.

Contrary to our recommendation, the next samples provided for analysis were mid view of material with pixel spacing 1.199 um

# AI Development

# AI Development – Phase 1

**Phase 1: First set of 9 samples without ground truth (25.10.2021)**

Hyundai Motors provided a total of 9 samples of different thermal insulation materials.

| Materials | 2 | 3 | 5 | 4 | 6 |
|---|---|---|---|---|---|
| Dimensions | 2102x2438 | 2306x2386 | 2500x2856 | 2241x2481 | 2172x2077 |
| Pixel Spacing (μm) | 1.199\1.199 | 1.199\1.199 | 1.200\1.200 | 1.199\1.199 | 1.199\1.199 |
| Total no. of Slices | 777 | 1212 | 1879 | 1255 | 1265 |
| No. of slices containing material | 400 | 800 | 1479 | 850 | 860 |
| Depth of material covered = No. of slices containing material * pixel spacing (μm) | 400*1.199 = 479.6 | 800*1.199 =959.2 | 1479*1.2 = 1791.6 | 850*1.199 = 1019.15 | 860*1.199=1031.14 |

| Materials | 7 | 8 | 9 | 10 |
|---|---|---|---|---|
| Dimensions | 2655x2820 | 2424x2476 | 2489x2451 | 2260x2192 |
| Pixel Spacing (μm) | 1.199\1.199 | 1.199\1.199 | 1.199\1.199 | 1.199\1.199 |
| Total no. of Slices | 1205 | 1198 | 1130 | 1297 |
| No. of slices containing material | 800 | 700 | 700 | 800 |
| Depth of material covered = No. of slices containing material * pixel spacing (μm) | 800*1.199= 959.2 | 700*1.199=839.3 | 700*1.199 = 839.3 | 800*1.199=959.2 |

*Figure 8:Specifications of Materials*

# AI Development – Phase 1

Link to detailed document

Phase 1: First set of 9 samples without ground truth (25.10.2021)

***2D Element Segmentation:***

Initially 2D segmentation of elements was done using image processing techniques. At this stage, the fillers were only categorized into big and small fillers. And the criteria for classification of filler as big or small was based on visual analysis, where fillers having a diameter less than 13 micrometers approx. were categorized as

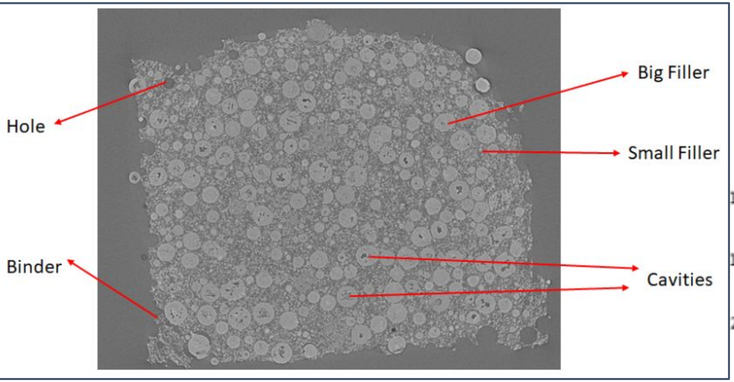



*Figure 10:Elements labelled for Material 2*

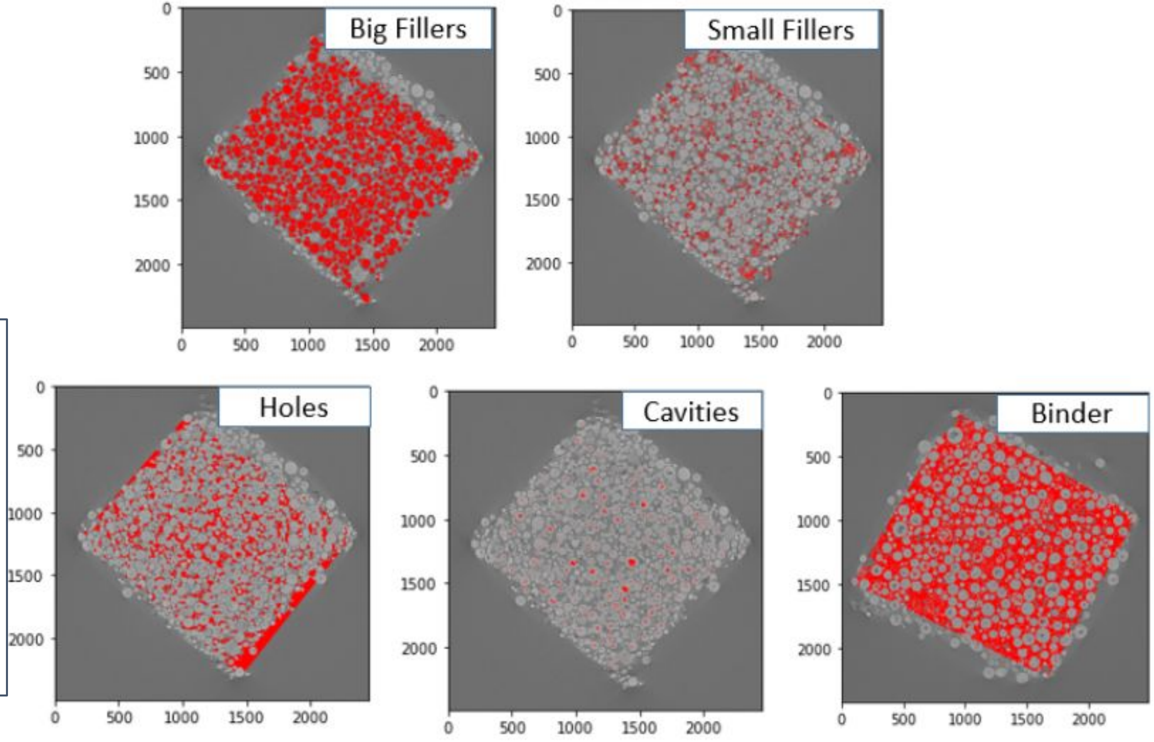



*Figure 9:Segmentation of Elements in Material 3*

# AI Development – Phase 1

Phase 1: First set of 9 samples without ground truth (25.10.2021)

*__2D Feature Extraction:__*

Possible Features were extracted for all materials and can be seen in figures.:

We also grouped the materials based on similar trends and the hypothesis was that the samples in same group will have similar properties values.

[Heat Transfer Paths 2D Doc](#)

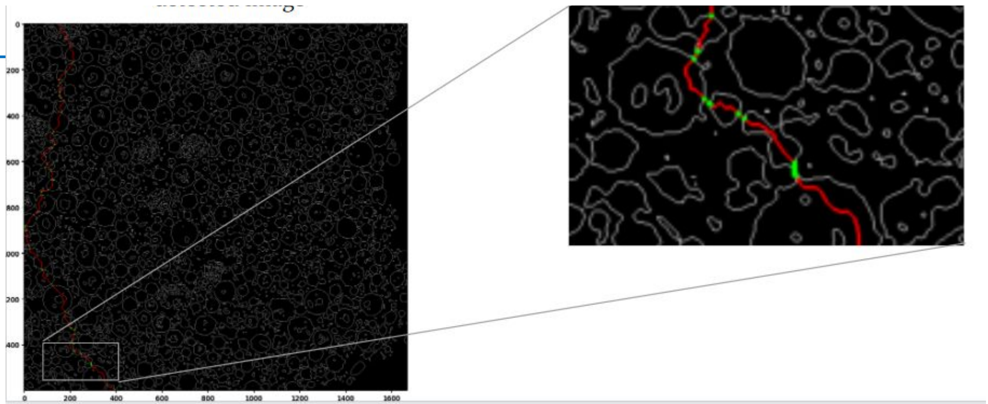


Figure 14:Heat transfer paths (HTPs) and contact points of each path with fillers

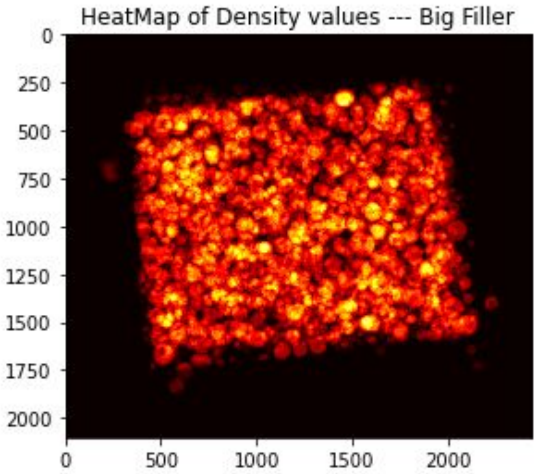



Figure 11: Density Heat Map of Big fillers

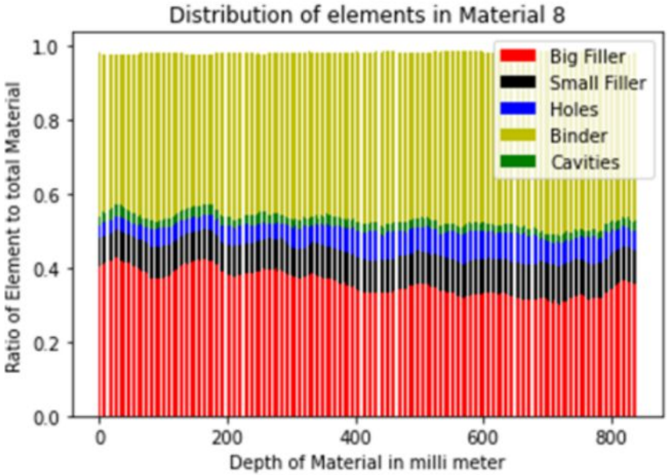



Figure 12:Distribution of Elements for Material 8

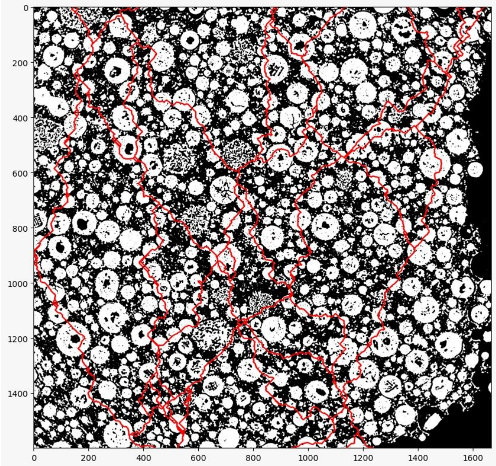



Figure 13:Heat transfer paths (HTPs)

# AI Development – Phase 1

[Heat Density map of elements of all materials](#)

**Phase 1: First set of 9 samples without ground truth (25.10.2021)**

***3D Element Segmentation:***

As the filler sizes were significant, we moved to 3D element Extraction. 3D extraction algorithm was developed, ratios were Computed and results were rendered as shown.

| Elements/ Material | Binder | Filler | Holes | Cavity |
| --- | --- | --- | --- | --- |
| Material 2 | 48.58 | 49.048 | 1.4733 | 0.97538 |
| Material 3 | 51.49766 | 47.011273 | 0.968 | 0.559624 |
| Material 4 | 48.5698 | 49.0986 | 0.946 | 1.4729 |
| Material 5 | 50.280 | 48.358 | 0.59616 | 0.818 |
| Material 6 | 51.1078 | 47.5332 | 0.645293 | 0.787371 |
| Material 7 | 45.6915 | 53.405897 | 0.29238 | 0.6228917 |
| Material 8 | 46.535780 | 50.747 | 1.320091 | 1.59504 |
| Material 9 | 43.7467433 | 51.0980559 | 3.7987 | 1.44513087 |
| Material 10 | 57.999 | 41.87 | 1.0077 | 0.0182 |

*Figure 16:Element Ratios*

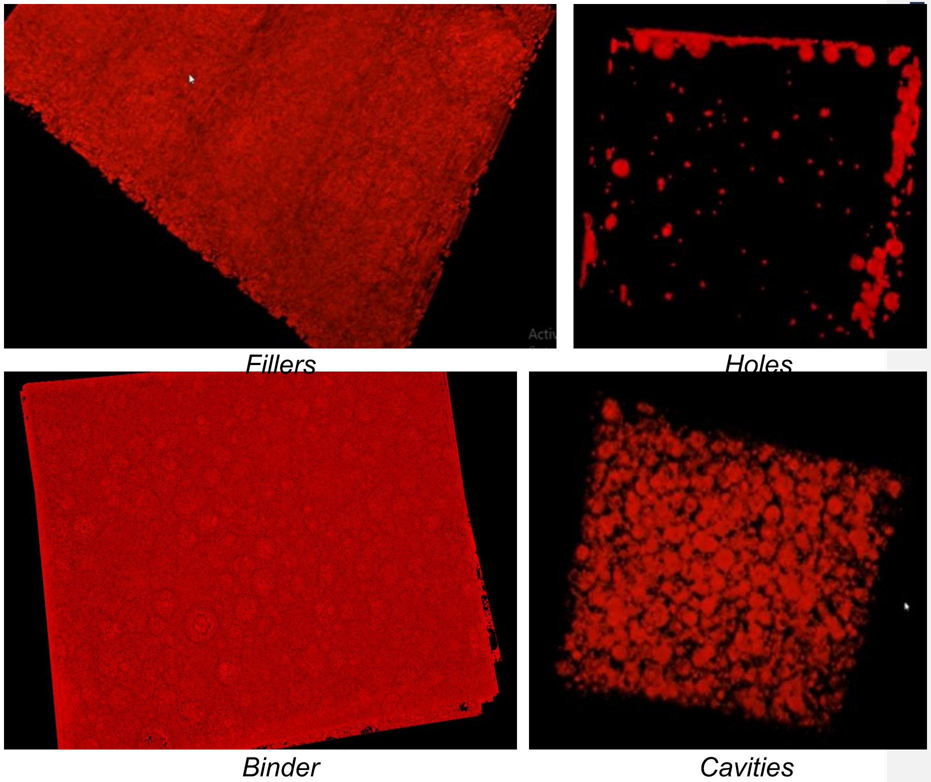



*Figure 15:3D rendered Elements after segmentation for Material 2*

# AI Development – Phase 1

**Phase 1: First set of 9 samples without ground truth (25.10.2021)**

***3D Filler Classification:***

Fillers are then divided into 3 subcategories based on their size: Small (5 ~70 micrometre), Medium (70~120 micrometre) and Big (120~120+ micrometre)

Fillers were classified, segmented and rendered as big, medium and Small fillers. Ratios were also computed and can be seen here.

| Material | Small filler | Medium filler | Big filler |
|---|---|---|---|
| Material no. 2 (400*1605*1881) | 41.006 | 24.550 | 34.443 |
| Material no. 3 (812*500*500) | 57.9955 | 16.325 | 25.678 |
| Material no. 4 (855*500*500) | 36.6544 | 34.292 | 29.0526 |
| Material no. 6 (865*500*500) | 38.164 | 14.3553 | 47.4797 |
| Material no. 7 (805*500*500) | 47.3155 | 30.4711 | 22.213 |
| Material no. 8 (798*500*500) | 23.3017 | 22.244 | 54.453 |
| Material no. 9 (730*500*500) | 34.751 | 40.768 | 24.479 |
| Material no. 10 (897*500*500) | 99.8575 | 0.1424 | 0.0 |

*Figure 18: Filler Ratios*

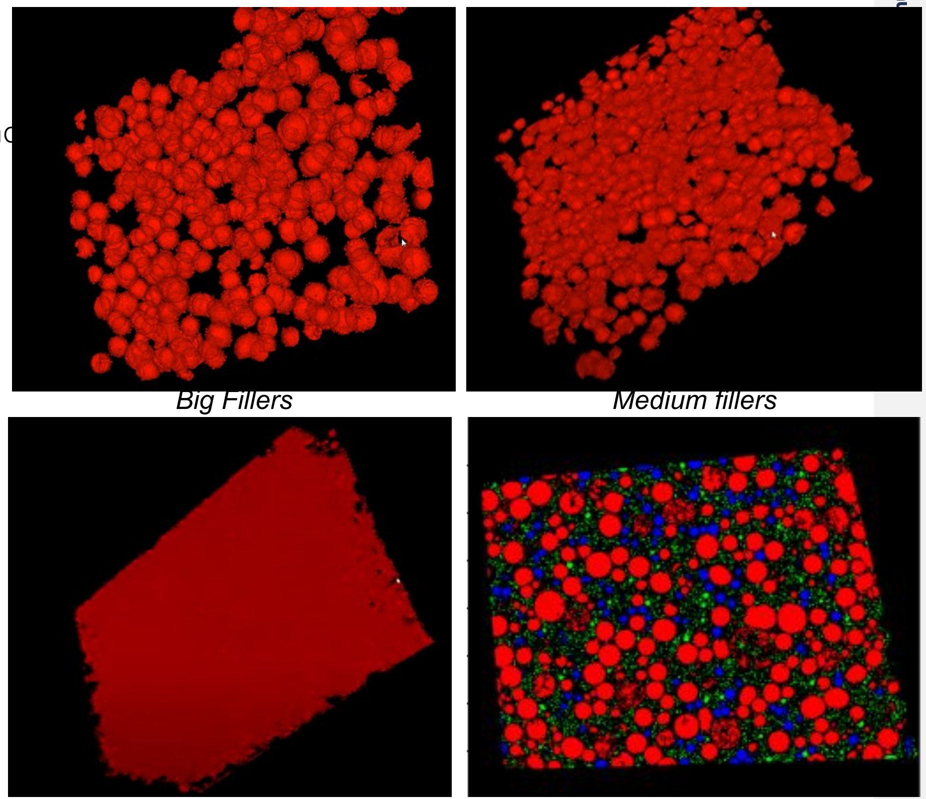



*Figure 17:3D rendered fillers for Material 2*

# AI Development – Phase 2

**Phase 2: 2nd Set of 9 samples with ground truth for all samples (15.02.2022)**

In 2nd phase, HMotors provided:

- CT scans of 9 more samples.
- Ground truth of property values for all materials.
- Ground truth of filler ratios. These filler ratios are before the manufacturing of thermal insulation materials based on the size of raw partic

| 총 필러 함량 內 각 사이즈 비율(%) | | | |
|---|---|---|---|
| No. | 5㎛ 사이즈 | 70㎛ 사이즈 | 120㎛ 사이즈 |
| 1 | 0 | 0 | 100 |
| 2 | 33.33 | 33.33 | 33.33 |
| 3 | 66.67 | 16.67 | 16.67 |
| 4 | 16.67 | 66.67 | 16.67 |
| 5 | 0 | 50 | 50 |
| 6 | 50 | 0 | 50 |
| 7 | 50 | 50 | 0 |
| 8 | 16.67 | 16.67 | 66.67 |
| 9 | 0 | 100 | 0 |
| 10 | 100 | 0 | 0 |

*Figure 19: Ground truth for Filler particle Ratios*

| No. | 열전도율 (W/mK) | 비중 | 내전압 (mA) |
|---|---|---|---|
| 1 | 측정불가 | 측정불가 | 측정불가 |
| 2 | 1.67 | 2.344 | 0.221 |
| 3 | 1.57 | 2.356 | 0.137 |
| 4 | 1.94 | 2.359 | 0.173 |
| 5 | 0.08 | 2.318 | 0.168 |
| 6 | 1.84 | 2.344 | 0.146 |
| 7 | 1.51 | 2.333 | 0.14 |
| 8 | 1.44 | 2.349 | 0.122 |
| 9 | 0.21 | 2.347 | 0.142 |
| 10 | 1.37 | 2.325 | 0.131 |

*Figure 20: Ground Truth for physical properties*

# AI Development – Phase 2

**Phase 2: 2nd Set of 9 samples with ground truth for all samples (15.02.2022)**

We computed all the features for new samples and the ratio values can be seen below.

Element ratios of all samples were close to the ground truth i.e 50:50 filler to binder volumetric ratio.

Whereas, the filler ratios after classification of fillers were not justifiable for some materials when compared to ground truth. For instance material 9 should have 0% small fillers while we were getting a significant ratio of small fillers i.e. 47.31.

H Motors then provided another set of scans.

| Elements/ Material | Binder | Filler | Holes | Cavity |
|---|---|---|---|---|
| Material 2 | 44.4902 | 50.32 | 4.170 | 1.08301 |
| Material 3 | 44.2748 | 55.027 | 0.248461 | 0.4660 |
| Material 4 | 46.709 | 50.653 | 1.479 | 1.20535 |
| Material 6 | 44.5234 | 53.741 | 1.070535 | 0.72778 |
| Material 7 | 45.02138 | 53.9128 | 0.41133 | 0.702 |
| Material 8 | 45.4771 | 50.952455 | 2.55872 | 1.1682 |
| Material 9 | 35.5460 | 46.18 | 17.44062 | 0.866412 |
| Material 10 | 53.76913 | 46.08396 | 0.11965 | 0.119 |

*Figure 21: Element Ratios*

| New Material | Small filler | Medium filler | Big filler |
|---|---|---|---|
| Material no. 2 (378*500*500) | 32.8 | 19.63 | 47.55 |
| Material no. 3 (837*500*500) | 60.16 | 14.45 | 25.38 |
| Material no. 4 (901*500*500) | 33.06 | 37.43 | 29.49 |
| Material no. 6 (857*500*500) | 43.28 | 9.38 | 47.32 |
| Material no. 7 (821*500*500) | 51.73 | 31.26 | 16.99 |
| Material no. 8 (821*500*500) | 23.29 | 23.14 | 53.55 |
| Material no. 9 (903*500*500) | 47.31 | 37.65 | 15.031 |
| Material no. 10 (789*500*500) | 99.18 | 0.65 | 0.15 |

*Figure 22: Filler ratios after classification*

# AI Development – Phase 3



## Phase 3: 3rd Set of 9 samples (28.02.2022)

Based on our filler classification analysis, HMotors provided another set of 9 CT scans for the same materials along with the same ground truth. The computed ratios can be seen below:

| Material No. | Fillers | Binder | Cavities | Holes |
|---|---|---|---|---|
| Material 2 | 0.436 | 0.5083 | 0.00969 | 0.0468 |
| Material 3 | 0.3252 | 0.6206 | 0.00455 | 0.0499 |
| Material 4 | 0.4348 | 0.482 | 0.00889 | 0.0748 |
| Material 5 | 0.370121 | 0.42274 | 0.004928 | 0.202245 |
| Material 6 | 0.3942 | 0.5419 | 0.00469 | 0.0594 |
| Material 7 | 0.3751 | 0.5098 | 0.005799 | 0.1095 |
| Material 8 | 0.4746 | 0.4523 | 0.006053 | 0.067514 |
| Material 9 | 0.4588 | 0.34564 | 0.01367 | 0.18286 |

*Figure 23: Element Ratios*

| Material No. | Small fillers | Medium fillers | Big fillers |
|---|---|---|---|
| Material 2 | 31.57 | 26.13 | 42.3 |
| Material 3 | 46.17 | 20.59 | 33.24 |
| Material 4 | 36.46 | 36.63 | 26.91 |
| Material 5 | 45.25 | 33.76 | 20.94 |
| Material 6 | 42.42 | 15.91 | 41.67 |
| Material 7 | 42.12 | 34.29 | 23.59 |
| Material 8 | 32.31 | 24.64 | 43.06 |
| Material 9 | 34.88 | 42.36 | 22.76 |

*Figure 24: Filler ratios after classification*

# AI Development – Phase 3

Phase 3: 3rd Set of 9 samples (28.02.2022)

[Link to detailed documentation](#)

*Analysis of component ratios:*

We analysed the computed ratios and observed the following:

- We don't get exact 50:50 for fillers : binder, where the binder (i.e. binder+holes) ratio computed by our algorithm is always more than 50%.
- The percentage of cavities is very low but holes have a significant ratio in some samples (for example sample 2 and sample 3 of material 5 and 9)
- The ratios of small, medium and big filler do not match with the ground truth as the ground truth is before mixing and mixing seems to change the ratios because of agglomeration filler particles.

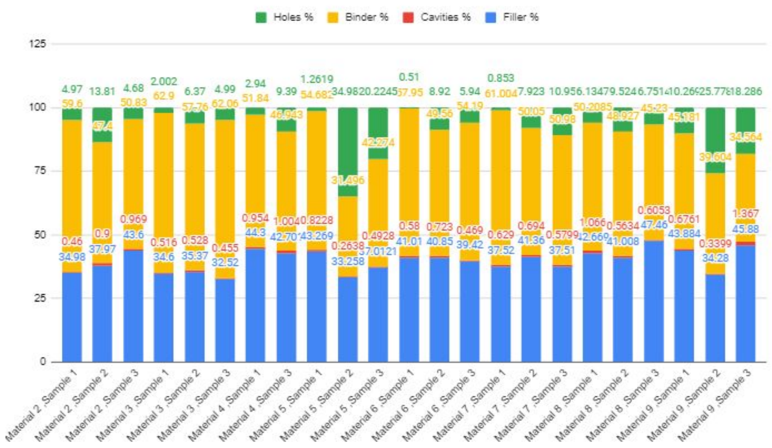



*Figure 23: Stacked Column chart of Predicted Element ratios for all samples*

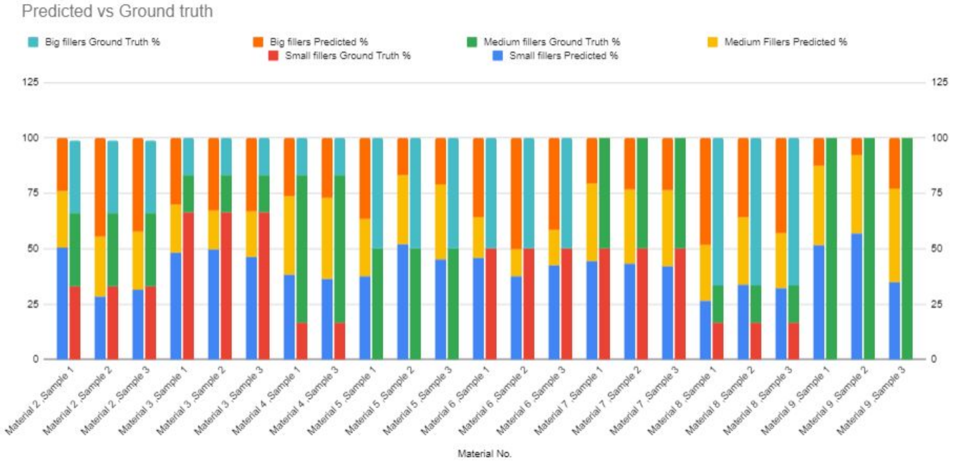



*Figure 24: Stacked Column chart of Predicted Filler (small, mid, big) ratios along with ground truth for all samples*

# AI Development – Phase 3

**Phase 3: 3rd Set of 9 samples (28.02.2022)**

***<u>3D Heat transfer Paths (HTPs):</u>***

As heat transfer is a 3D phenomenon, we developed a new algorithm to find heat transfer paths in 3D. The rendered results from different HTP experiments can be seen here.

Mid term report having detailed documentation was delivered.

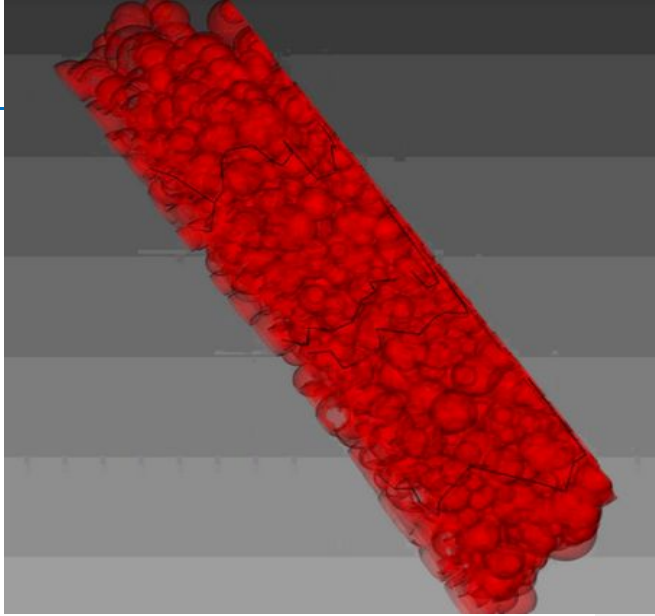


*Figure 25: 3D rendering of 5 HTPs on whole material (size: 400*1605*1881)*

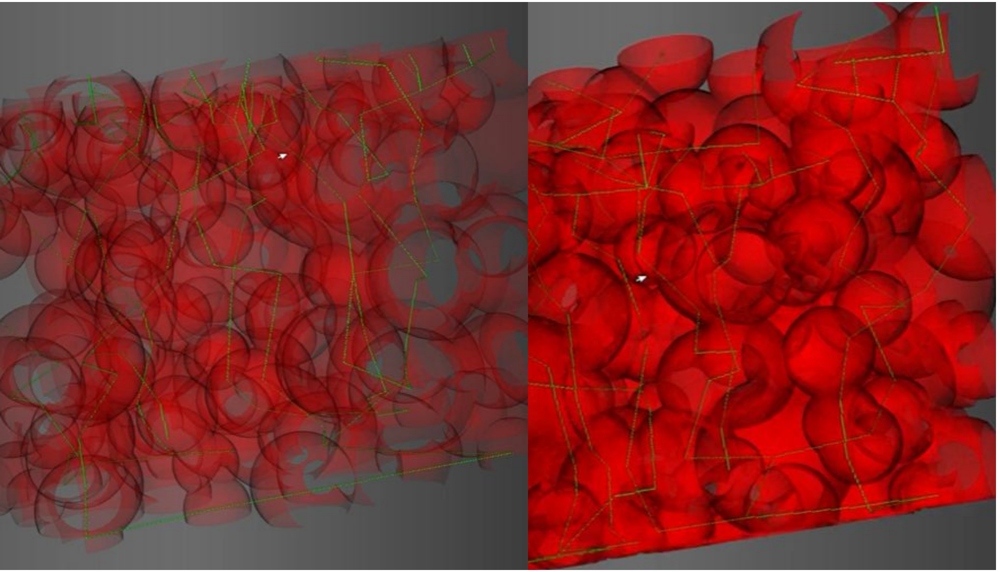


*Figure 27: 3D Rendering of all possible paths (only nearest binder to centroid of filler)*

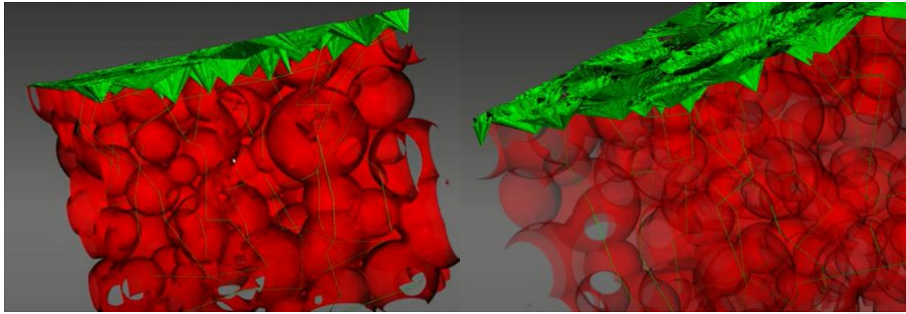


*Figure 26: 3D Rendering of all possible heat transfer paths (including all binders)*

# AI Development – Phase 3



Link to detailed document

Phase 3: 3rd Set of 9 samples (28.02.2022)

***3D Heat transfer Paths (HTPs):***

Heat transfer path connects nearest neighboring fillers to make a path from top to bottom. We developed two different variations of algorithm to find the HTPs.

- HTP is formed by connecting each filler to nearest neighbor, where the two fillers can be parallel to each other (i.e. have an angle of zero degrees as shown in fig. 28.
- HTP is formed by connecting each filler to nearest neighbor, where the two fillers cannot be parallel to each other (i.e. have an angle greater than zero degrees as shown in fig. 29.

Both these variations were then used to compute the thermal conductivity values.

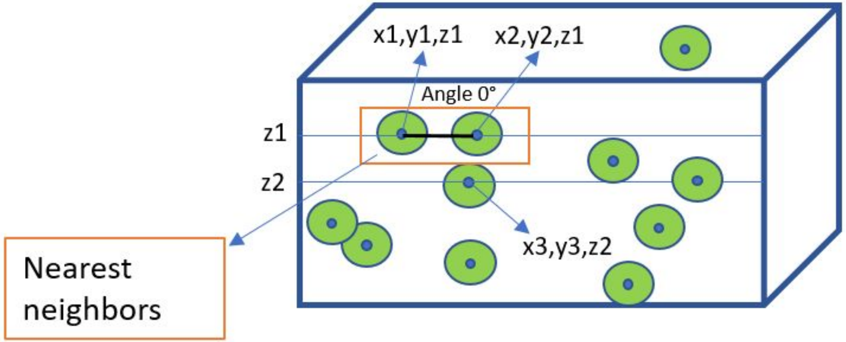



*Figure 28: Parallel Neighbors algorithm (variation - 1)*

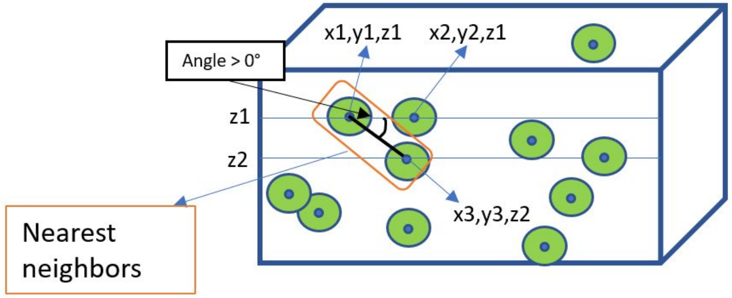



*Figure 29: Downward Neighbor algorithm (variation - 2)*

# AI Development – Phase 3

Phase 3: 3rd Set of 9 samples (28.02.2022)

***Thermal Conductivity Prediction***

We performed literature review and found a mathematical model for thermal conductivity using heat transfer paths in a material.
The effective thermal conductivity of the composite can be calculated by:

$$k_e = \frac{k_m k_f}{V_d k_m + (1 - V_d) k_f} \frac{V_f}{V_d} \left(\frac{L}{s}\right)^2 + \left[\frac{L}{s} - \frac{V_f}{V_d}\left(\frac{L}{s}\right)^2\right] k_m$$

Where:

- km = thermal conductivity of binder
- kf = thermal conductivity of fillers
- Vd = Volume fraction of fillers in a Heat Transfer Path
- Vf = Volume fraction of fillers.
- L = thickness of the sample
- s = mean length of  a Heat Transfer Path

Thermal Conductivity of material can be found by taking the mean of ke calculated for each Heat Transfer Path.

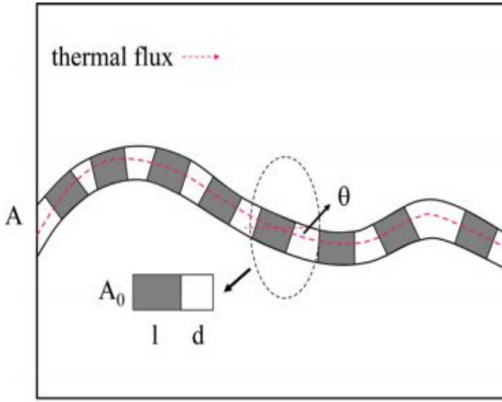



*Figure 30: The model of Heat Transfer Passage*

Visual representation of the model of heat transfer path. The gray shadowing region indicates the filler region in the path and the white blank area is the binder. In the figure,

- L = thickness of the sample
- A = cross-section area of the sample perpendicular to the direction defined by the thermal flow
- Ao = cross-section area of the Heat Transfer Paths
- l = mean length along the Heat Transfer Paths of fillers
- d = mean distance between particles along a Heat Transfer Path
- Θ = angle between the axis of Heat Transfer Paths and the direction defined by thermal flow

# AI Development – Phase 3

**Phase 3: 3rd Set of 9 samples (28.02.2022)**

***Thermal Conductivity Prediction***

- In case of our analysis:
  - km = 1.2 W/mK for Silicon resin
  - kf = 40 W/mK for $Al_2O_3$
- We got the values of Vf, Vd, L, s by developing the required algorithms using image processing techniques.
- The implementation of this model for our material can be seen in fig. 31.
- For thermal conductivity of material:
- L is the thickness of material (i.e. the number of slices), the value for Vf is the filer ratio in material.
- Values of Vd, s, L, km and kf are put in the formula of ke to predict thermal conductivity of each path. For the whole material ke of all the paths are taken and the average value is calculated.
- We computed thermal conductivity Ke values on patches of whole material due to computational constraints and then averaged the values.
- We, then, optimised the code to compute the Ke value on whole material.

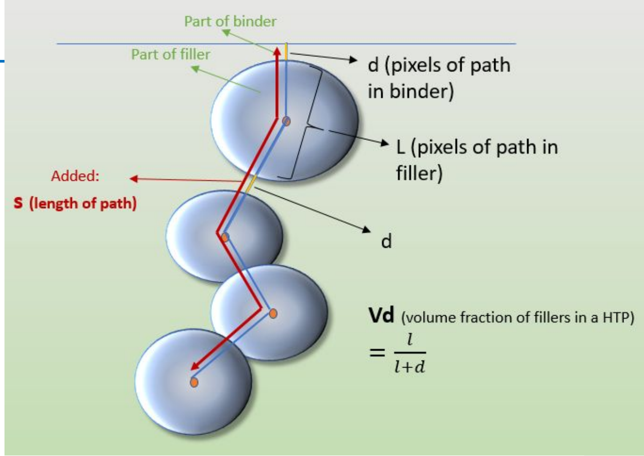



*Figure 31: Implementation of HTPs model*

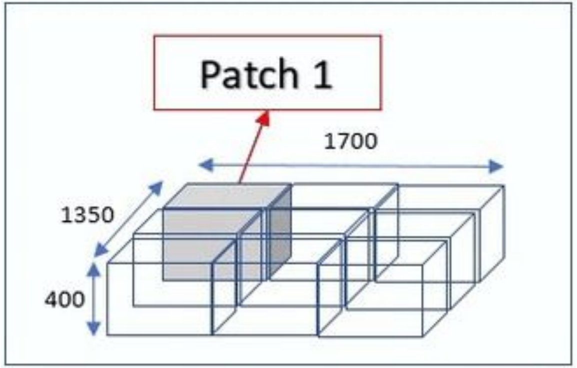



*Figure 32: Visualisation of Patches of a material*

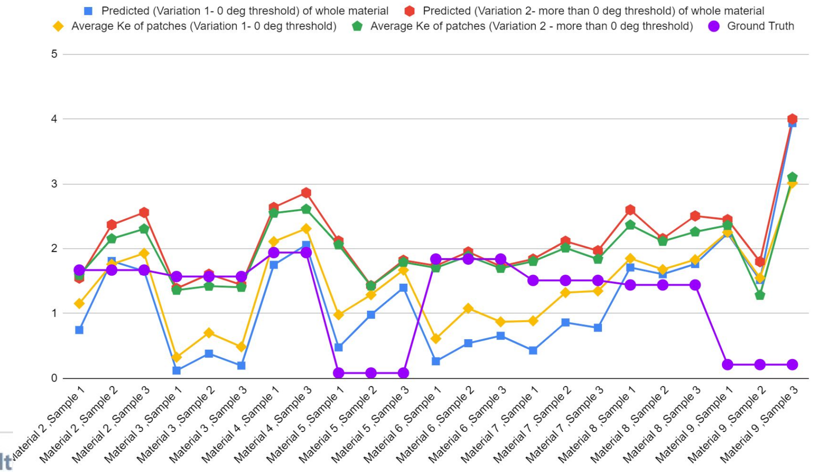
# AI Development – Phase 3

[Link to detailed documentation](#)

Phase 3: 3rd Set of 9 samples (28.02.2022)

***Thermal Conductivity Prediction***

- The computed values of thermal conductivity for all sample scans can be seen in the table.
- We then analysed all the results and concluded that the computed thermal conductivity values using the analytical approach after finding Heat transfer paths (HTPs) are very sensitive.
- The Heat Transfer Paths (HTPs) can only be used for thermal conductivity and not for the other properties.
- Based on our analysis, we moved on to ML/DL based approaches for property prediction.




| | Thermal Conductivity (Ke) | | | | |
|---|---|---|---|---|---|
| Material No. | Predicted (Variation 1- 0 deg threshold) of whole material | Predicted (Variation 2- more than 0 deg threshold) of whole material | Average Ke of patches (Variation 1- 0 deg threshold) | Average Ke of patches (Variation 2 - more than 0 deg threshold) | Ground Truth |
| Material 2 ,Sample 1 | 0.744 | 1.546 | 1.153 | 1.588 | 1.67 |
| Material 2 ,Sample 2 | 1.81 | 2.37 | 1.76 | 2.154 | 1.67 |
| Material 2 ,Sample 3 | 1.654 | 2.559 | 1.929 | 2.305 | 1.67 |
| Material 3 ,Sample 1 | 0.118 | 1.386 | 0.3242 | 1.359 | 1.57 |
| Material 3 ,Sample 2 | 0.379 | 1.606 | 0.701 | 1.422 | 1.57 |
| Material 3 ,Sample 3 | 0.194 | 1.442 | 0.4843 | 1.4043 | 1.57 |
| Material 4 ,Sample 1 | 1.751 | 2.637 | 2.11 | 2.55 | 1.94 |
| Material 4 ,Sample 3 | 2.058 | 2.864 | 2.31 | 2.61 | 1.94 |
| Material 5 ,Sample 1 | 0.4758 | 2.1191 | 0.979 | 2.06 | 0.08 |
| Material 5 ,Sample 2 | 0.9802 | 1.4296 | 1.289 | 1.425 | 0.08 |
| Material 5 ,Sample 3 | 1.3978 | 1.821 | 1.67 | 1.791 | 0.08 |
| Material 6 ,Sample 1 | 0.2609 | 1.737 | 0.611 | 1.705 | 1.84 |
| Material 6 ,Sample 2 | 0.54 | 1.95 | 1.079 | 1.888 | 1.84 |
| Material 6 ,Sample 3 | 0.655 | 1.727 | 0.871 | 1.698 | 1.84 |
| Material 7 ,Sample 1 | 0.428 | 1.84 | 0.885 | 1.805 | 1.51 |
| Material 7 ,Sample 2 | 0.8608 | 2.115 | 1.322 | 2.012 | 1.51 |
| Material 7 ,Sample 3 | 0.779 | 1.969 | 1.347 | 1.839 | 1.51 |
| Material 8 ,Sample 1 | 1.71 | 2.6 | 1.849 | 2.367 | 1.44 |
| Material 8 ,Sample 2 | 1.606 | 2.156 | 1.679 | 2.115 | 1.44 |
| Material 8 ,Sample 3 | 1.763 | 2.506 | 1.831 | 2.26 | 1.44 |
| Material 9 ,Sample 1 | 2.237 | 2.449 | 2.254 | 2.361 | 0.21 |
| Material 9 ,Sample 2 | 1.517 | 1.799 | 1.549 | 1.281 | 0.21 |
| Material 9 ,Sample 3 | 3.94 | 4.003 | 3.015 | 3.104 | 0.21 |

# AI Development – Phase 3

Link to detailed documentation

**Phase 3: 3rd Set of 9 samples (28.02.2022)**

***DL/ML based Property Prediction Model***

*Data distribution:*

- Training: All 3 samples of Material 2, 4, 5, 6, 7 and 9
- Testing: All 3 samples of Material 3 and 8

*Input Features:*

- Cavity ratio
- Holes ratio
- Filler ratio
- Binder ratio
- Small filler ratio
- Medium filler ratio
- Large filler ratio

Initial experimentation and results can be seen in fig. 33.
We also performed performed K Means Clustering using Density Heat maps to group together the samples showing similar property values or similar component ratios, but no pattern was found and the AI failed to perform the desired clustering.

| Model | Property | Avg. Percentage Error |
|---|---|---|
| CNN having 2 linear layers | Viscosity | 0.61% |
| | Withstand Voltage | 24.05% |
| | Thermal Conductivity | 24.09% |
| CNN having 2 linear layers but multiplied the values by 10 to increase the loss generated by a slight error | Viscosity | 0.30% |
| | Withstand Voltage | 24.21% |
| | Thermal Conductivity | 27.05% |
| CNN having 2 linear layers but with normalisation of all values | Viscosity | 0.33% |
| | Withstand Voltage | 26.76% |
| CNN having 4 linear layers | Viscosity | 0.52% |
| | Withstand Voltage | 25.55% |
| Sklearn's tree regressor | Viscosity | 0.55% |
| | Withstand Voltage | 55.55% |

*Figure 33: Initial DL/ML experimentation*

# AI Development – Phase 3



Phase 3: 3rd Set of 9 samples (28.02.2022)

***DL/ML based Property Prediction Model***

After low performance of previous experiments, **we limited the scope of project to prediction of only thermal conductivity and withstand voltage. Viscosity prediction was excluded.**

We divided the materials into bins and performed classification using random forest classifier and Elements (Fillers, Binder, Holes and cavities) to whole material ratios as features.

Bins for thermal conductivity:

| Bin1 | Bin2 | Bin3 | Bin4 |
|---|---|---|---|
| 0.08 (Material 5) | 1.44 (Material 8) | 1.51 (Material 7) | 1.84 (Material 6) |
| 0.21 (Material 9) | | 1.57 (Material 3) | 1.94 (Material 4) |
| | | 1.67 (Material 2) | |

Achieved accuracy: 75% accuracy was achieved with 3 fold cross validation

Bins for withstand voltage:

| Bin1 | Bin2 | Bin3 | Bin4 | Bin5 | Bin6 |
|---|---|---|---|---|---|
| 0.122 (Material 8) | 0.137 (Material 3) | 0.14 (Material 7) | 0.168 (Material 5) | 0.173 (Material 4) | 0.221 (Material 2) |
| | | 0.142 (Material 9) | | | |
| | | 0.146 (Material 6) | | | |

Achieved accuracy: 66% accuracy was achieved with 3 fold cross validation

# AI Development – Phase 4

Link to detailed documentation

**Phase 4: 4th set of 27 new Samples (01.08.2022)**

HMotors provided new samples with the same ground truth.

We tested the performance of our developed classification AI on the new dataset.
Performance of the model decreased as the cross fold accuracy values dropped.

- Thermal conductivity average cross fold accuracy decreased from 75% to 66%
- Withstand voltage average cross fold accuracy decreased from 66% to 54%

Upon analysis, we found that the reason of drop in performance is that some materials have visible cracks in them as shown in fig.

This leads to inconsistency in elements to whole material ratios, as the cracks are classified as holes.

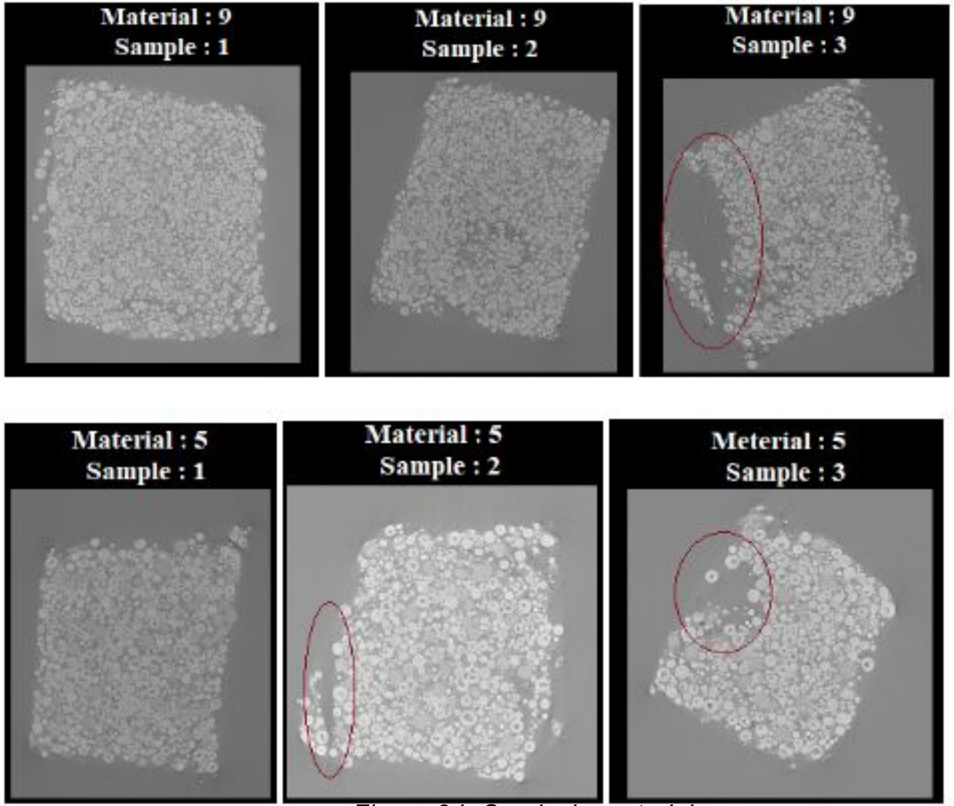



*Figure 34: Cracks in materials*

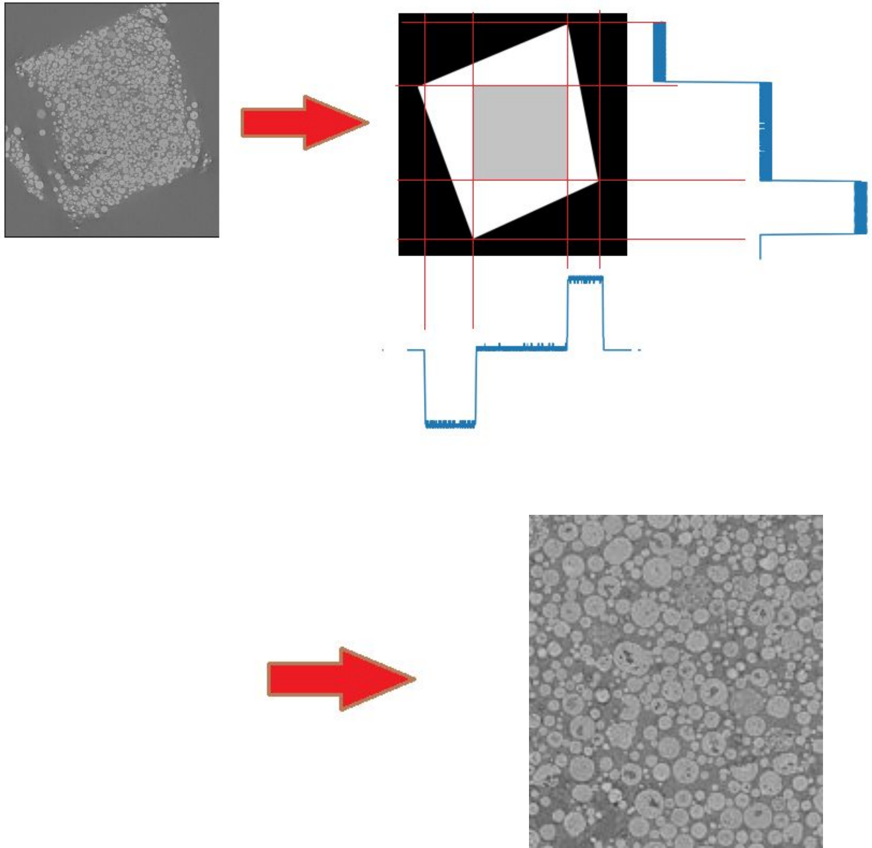
# AI Development – Phase 4

[Link to detailed documentation](#)

**Phase 4: 4th set of 27 new Samples (01.08.2022)**

To remove the cracked patches

- We first generate the mask for materials. To generate mask:-
    - First blurring the image
    - Second applied thresholding
    - Select the biggest area
- Second we plotted the gradient ( in blue plot on side of mask) for height and width of mask to check slopes. Slopes are removed because you can see their are still cracks on boundary of image Gradient helps to remove these type of cracks.
- Finally we crop the area shown in gray color in mask image.



# AI Development – Phase 4

**Phase 4: 4th set of 27 new Samples (01.08.2022)**

- After cropping the cropped scans have consistent filler densities but binder, cavities and holes densities are affected. Due to this issue we only used filler densities.
- The red circle in figure 35 shows binders and hole densities missed while cropping

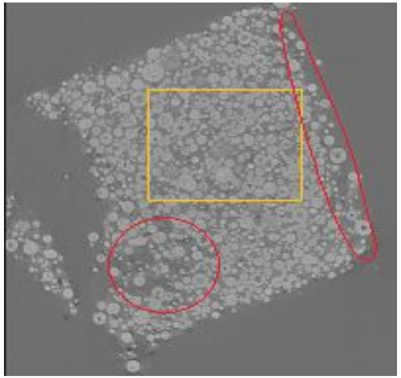


*Figure 35: Material Copping*

- We trained a decision tree regressor on old scans and used this model to predict properties of new scans
- .average % mean eror
- Thermal conductivity = 0.1788%
- Withstand voltage = 0.04611348%

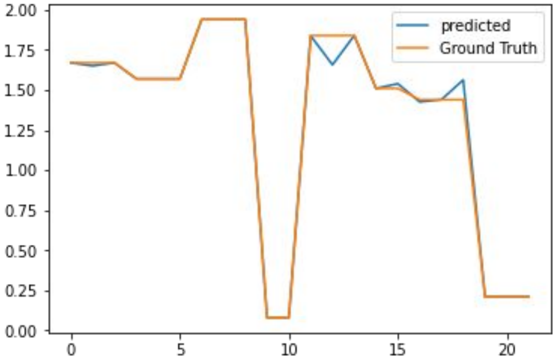



*Figure 36: AI performance for thermal conductivity*

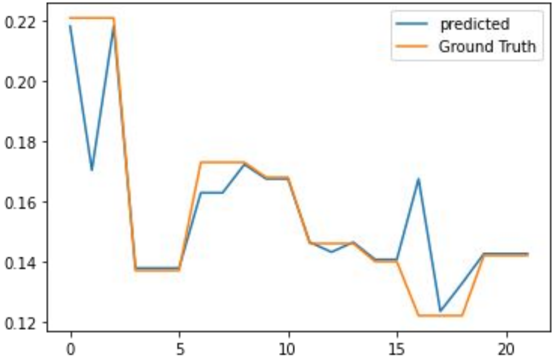



*Figure 37: AI performance for withstand voltage*

# AI Development – Phase 4

Percentage mean error for experiment explained in previous slide.

### % mean error Thermal conductivity

| material | % Mean error |
|---|---|
| 2.1 | 0.0035125756 |
| 2.2 | 0.8136942546 |
| 2.3 | 0.0035125756 |
| 3.1 | 0.0010929755 |
| 3.2 | 0.0010929755 |
| 3.3 | 0.0010929755 |
| 4.1 | 0.0458449788 |
| 4.2 | 0.0458449788 |
| 4.3 | 0.0014225887 |
| 5.1 | 0.0516844087 |
| 5.2 | 0.0516844087 |
| 6.1 | 0.0784500365 |
| 6.2 | 9.8187317699 |
| 6.3 | 0.1007160546 |
| 7.1 | 0.0005264577 |
| 7.2 | 2.5475484892 |
| 8.1 | 0.7212834897 |
| 8.2 | 0.0007479868 |
| 8.3 | 8.8687730192 |
| 9.1 | 0.0201887541 |
| 9.2 | 0.0201887541 |
| 9.3 | 0.0201887541 |

### % mean error Withstand Voltage

| material | % Mean error |
|---|---|
| 2.1 | 1.2444010829 |
| 2.2 | 23.1328393668 |
| 2.3 | 1.2444010829 |
| 3.1 | 0.5917743810 |
| 3.2 | 0.5917743810 |
| 3.3 | 0.5917743810 |
| 4.1 | 11.5591667116 |
| 4.2 | 11.5591667116 |
| 4.3 | 0.4134975699 |
| 5.1 | 0.2996398836 |
| 5.2 | 0.2996398836 |
| 6.1 | 0.2939797791 |
| 6.2 | 2.0672066328 |
| 6.3 | 0.2939797791 |
| 7.1 | 0.4882553051 |
| 7.2 | 0.4882553051 |
| 8.1 | 37.2922991766 |
| 8.2 | 1.1857362919 |
| 8.3 | 7.7226156545 |
| 9.1 | 0.4216726131 |
| 9.2 | 0.4216726131 |
| 9.3 | 0.4216726131 |

# AI Development – Phase 4

**Phase 4: 4th set of 27 new Samples (01.08.2022)**

1. We have performed another experiment to check model's **robustness on unseen materials** .
2. The environment for experimentation is that we keep all samples for a material hidden from network and train it on rest of materials and ask this network to predict property of unseen material. We repeat this experiment by hiding each material one by one.
3. When we tested by providing only filler densities model was not able to predict trend that well shown in figure.
4. Secondly we discarded all scans with cracks and used filler, binder, holes and cavities densities as features
5. Model with these features predict **Thermal conductivity trend very well** as shown in figure
6. But **withstand voltage trend was not learned** by the model even with these features
7. **As model shows Robustness in Thermal conductivity prediction with all features we will check if there are no cracks we will use all features otherwise only filler densities will be provided to AI model.**

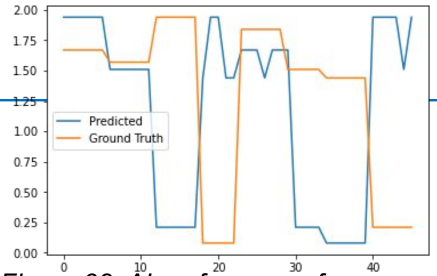


*Figure 38: AI performance for unseen thermal conductivity with fillers features*

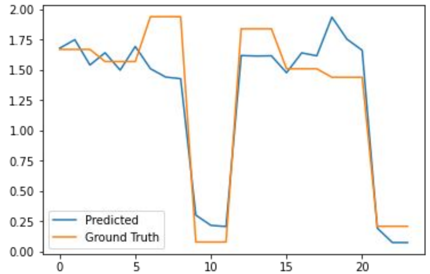


*Figure 39: AI performance for unseen thermal conductivity with all features*

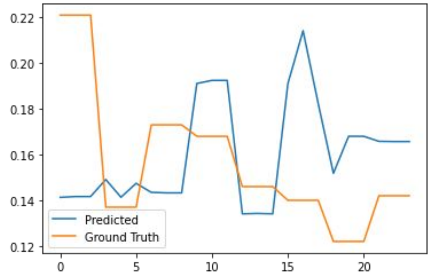


*Figure 39: AI performance for unseen Withstand voltage with all features*

# AI Development – Phase 4

Percentage mean error for experiment explained in previous slide.
average % mean error

- Thermal conductivity = 19.52%
- Withstand voltage = 6.773%

% mean error Thermal conductivity

| material | % Mean error |
|---|---|
| 2.1 | 0.5671500268 |
| 2.2 | 4.7083582781 |
| 2.3 | 7.7134341075 |
| 3.1 | 3.1188537369 |
| 3.2 | 4.4641391254 |
| 3.3 | 4.6462637504 |
| 4.1 | 22.4158508323 |
| 4.2 | 25.6732704731 |
| 4.3 | 26.3925052129 |
| 5.1 | 288.2976917317 |
| 5.2 | 172.3449171856 |
| 5.3 | 162.6863756898 |
| 6.1 | 11.8156033707 |
| 6.2 | 12.2570060375 |
| 6.3 | 11.9473802741 |
| 7.1 | 1.9427524842 |
| 7.2 | 9.2075409600 |
| 7.3 | 7.3190888583 |
| 8.1 | 34.3492097121 |
| 8.2 | 21.5439769136 |
| 8.3 | 15.7108834846 |
| 9.1 | 5.2029526614 |
| 9.2 | 63.7300498813 |
| 9.3 | 63.7300498813 |

% mean error Withstand Voltage

| material | % Mean error |
|---|---|
| 2.1 | 36.4282307456 |
| 2.2 | 36.4282307456 |
| 2.3 | 36.2780015118 |
| 3.1 | 8.8240012014 |
| 3.2 | 5.2921008019 |
| 3.3 | 7.5039948308 |
| 4.1 | 17.0942757229 |
| 4.2 | 17.0942757229 |
| 4.3 | 17.0942757229 |
| 5.1 | 13.1006996043 |
| 5.2 | 13.2088508892 |
| 5.3 | 13.2088508892 |
| 6.1 | 8.0282469594 |
| 6.2 | 8.3053002734 |
| 6.3 | 8.0282469594 |
| 7.1 | 53.9447015261 |
| 7.2 | 51.4677438067 |
| 7.3 | 6.0174820099 |
| 8.1 | 28.6543718071 |
| 8.2 | 37.7047656313 |
| 8.3 | 37.7047656313 |
| 9.1 | 14.3232793842 |
| 9.2 | 14.3232793842 |
| 9.3 | 14.3232793842 |

# App Development

# App Development

We developed an app using the following packages:

- Tkinter for 2D view
- PyQt and QVTK for 3D view

The app comprises of 3 screens:

- Screen 1 —> Analysis Board
- Screen 2 —> 2D visualisation and display of values from quantitative analysis
  and AI property predictions
- Screen 3 —> 3D visualisation

Details of main screen 1 including all the information about the design, functionalities of buttons etc are [here](#)

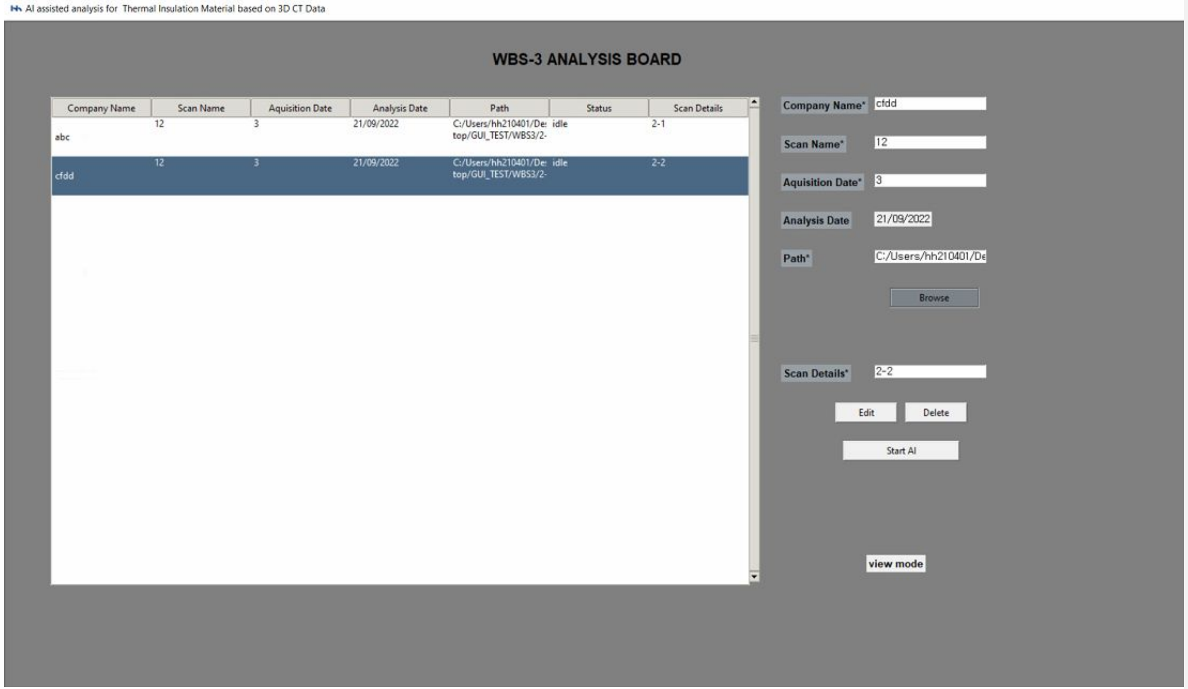



*Figure 38: Front end Screen 1:*

# App Development

Link to the demo for understanding the working of app can be found [here]

* The visualisations for demo are using the segmentation results and Element ratios from developed AI while dummy values are displayed for physical properties i.e. thermal conductivity and withstand voltage.

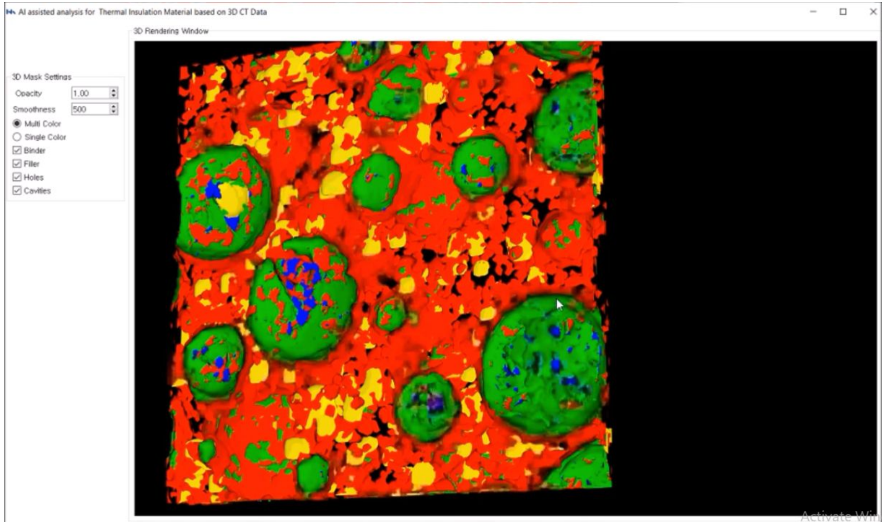



*Figure 39: Front End Screen 3*

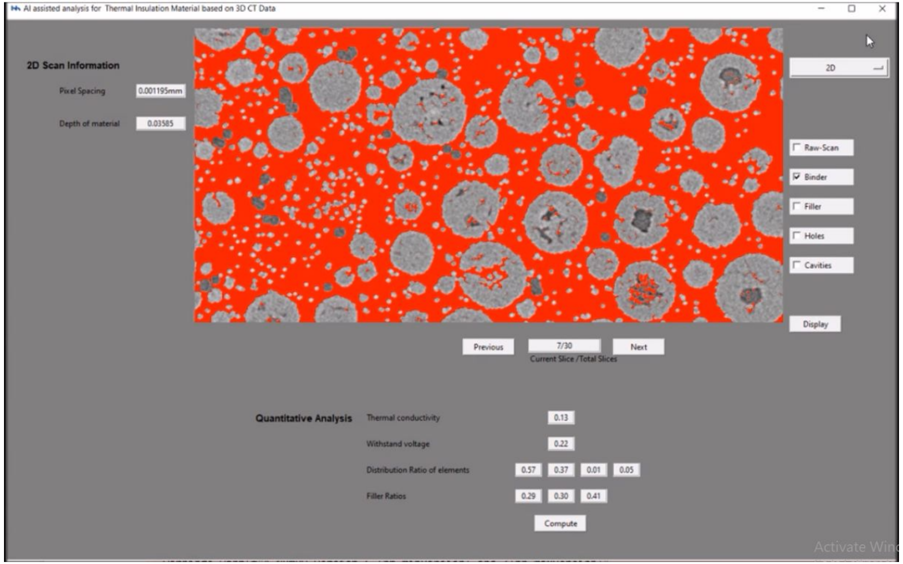



*Figure 40: Front End Screen 2*

# Performance/ Advantages of AI

# Performance/Advantages of AI

Following are the advantages of our developed AI:

- It accurately segments and quantifies all elements of the material.
- Gives satisfactory results for prediction of thermal conductivity and withstand voltage.
- The AI performs classification of fillers as well and provides quantification of Big, Medium and small fillers.
- It also provides improved visualisation of all elements through 3D rendering.

# Limitations of AI

# Limitations of AI

Following are some limitations of the developed AI:

- Although the AI only takes 15 seconds once the features are computed, the segmentation and computation of features takes more time.
- The AI has been developed using the scans of total 9 material and thus only 9 labels for each property. This results in less diversity in data. A more diverse data can help achieve even better performance.

# Conclusion

# Conclusion

We successfully developed an AI based application to visualise segmented material scans along with component ratios and predicted physical properties (thermal conductivity and withstand voltage) values.

# THANKS!

Any Questions?