Evaluation of Oscillatory Activation Functions on Retinal Fundus Multi-disease Image Dataset (RFMiD)

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Abstract

Recent studies in biological neurons have suggested existence of oscillatory activation functions, capable of solving the XOR problem individually. The mathematical representations of these functions have shown promising results on vision tasks when compared to the commonly used activations such as Swish, Mish and varaints of PReLU. Although many open source datasets provide good insights on their performances, specific use cases of these functions in architectures to solve domain specific problem with their relevant metrics is not covered. Medical image datasets often provide a valuable convention as the scope for error in the results is expected to be low, and they have specific criterions which needs to be improved as per the problem at hand. The common neural network backbones could be modified for hyperparameterizing the activation functions used in them to measure the capacity in which these new oscillating activation functions can be used in these datasets. In our task, we evaluate the performance of a family of activation functions on Retinal Fundus Multi-disease Image Dataset (RFMiD), which is a multi-label dataset for 46 conditions, using VGG, DesNet, MobileNet and EfficientNet. We also observe the performances on the subsets of these labels for better benchmarking. Based on our empirical evaluation we see that leveraging oscillatory activation functions allows a performance gain which showcases x percent improvement over best performing montonic non-linear activation functions like ReLU, Swish, Mish and could potentially enable generalised models for retinal screening that can help in classifying a number of sight threatening pathologies.

1 Introduction

Deep convolution neural networks have performed comparatively well across a variety of fields. Ranging from Computer Vision tasks pertaining to multi-class [19]/multi-label[20] image classification[18], image segmentation[23], image captioning[17], and GANs[6] for image enhancement[5], structured datasets where Machine Learning Frameworks and Neural Network(s) used in engine performance optimization[**?**], NLP tasks[21] such as sentence classification[7], token classification[15], question-answering[9], chatbots[2] and text generation[22] tasks. While a plethora of scientific datasets have been developed to serve as evaluation benchmarks for general purpose usecases, some of these are specifically targeted towards a given class of problems, used to design task-specific architecture(s)[3]. It is generally noticed that the medical, aerial, etc. datasets

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primarily have a very low tolerance for false positive and negative errors, hence these datasets are ideal for evaluating performance metrics.

Although some activation functions[16] may be more favourable over others in domain-specific tasks, recent work on oscillatory activation functions shows a promising stand on performing reasonably well in standardized datasets. This further leads to the question as to how effective these functions are when scoped in label/class imbalanced domains. Early studies around automatic activation selection [10] and self normalizing neural networks [8] suggest choice of activation function at various layers is a critical and often tedious task and could vary across variety of tasks such as drug discovery benchmarks and astronomy tasks. Some other popular methods of auto-explorations are also discussed in contextual bandits problems[**?**] where end to end automated meta-learning pipeline to approximate the optimal Q function and diversifying recommendation systems has been discussed. As exhaustive and reinforcement based approaches are able to identify novel activation functions for a particular architecture, their reliability across different models and datasets is unknown, although Linear Units (LUs) and its variations are proven to be reliable across many neural networks, there ponders a question whether oscillating activation functions are providing similar reliability across variety of architectures, and if so, what are the domain specific use-cases of these functions so that they can be better utilized for enhanced model metrics.

To obtain the right complexity in medical image analysis and validating the XOR problem[4] solution proposed by oscillatory activation functions, Retinal Fundus Multi-disease Image Dataset (RFMiD)[14] has been chosen as the primary data, having more than 46 labels for diverse eye conditions, some being rare in nature (sample size less than x percent) and will be solved as a multi-label problem. We have also chosen Diabetic retiopathy dataset[1] as secondary data, whose results will be validated as a multi-class problem. The intention is to holistically evaluate the merits of these oscillating activation functions in medical imaging usecases, and thereby showcase a value proposition around using these functions in further studies related to the medical domain.

In this paper, our contribution are three fold :-

- We introduce a novel benchmark on RFMiD medical imaging dataset for evaluating different model architectures.
- Showcase outputs on different subsets of the labels using a custom loss function.
- We leverage the novel oscillatory activation functions on various architectures and compare it to prior benchmarks

2 Oscillating Functions

Non-linear Activation functions are an integral component of neural network, used in deciphering the non-linearly separable data distributions. The choice of activation function [12] has an impact on the task specific performance of the given neural network. Despite the critical importance of the nature of these functions in determining the performance of neural networks, simple monotonic non-decreasing nonlinear activation functions are universally used. Neural networks suffer from a fundamental limitation where individual neurons can particularly exhibit linear decision boundaries. Multilayer neural networks with nonlinear activations are needed to achieve nonlinear decision boundaries. The newly proposed oscillatory nonlinear activation functions in deep neural networks is a family of functions that hold variety of properties pertaining to zero value approximation, differential and continuity behaviour, range and monotonicity[13], thus allowing individual neurons to exhibit nonlinear decision boundaries and removes the fundamental limitation of neural networks. In the past oscillatory [13] and non-monotonic activation functions have been largely ignored.

With monotonic activation functions, Neural Networks can be extended to control tasks

The reliability of an activation function is estimated by the following factors:-

- Scales well along with the size of the architecture
- Performance can be compared and could be deemed reliable based on a number of trials.
- Time and memory optimized, having minimal corner cases for variety of datasets.

Table 1: Properties of oscillatory activation functions

Activation Function	Equation	Continuity	Differentiablity	Monotonicity	Range
Sine	$f_{18}(z) = \sin(z)$	Yes	Yes	No	$[-1, 1]$
Cosine	$f_{18}(z) = \cos(z)$	Yes	Yes	No	$[-1, 1]$
Shifted Quadratic Unit (SQU)	$f_{19}(z) = z^2 + z$	Yes	Yes	No	$[-0.25, \infty)$
Monotonic Cubic	$f_{20}(z) = z^3 + z$	Yes	Yes	Yes	$(-\infty, \infty)$
Non-Monotonic Cubic Unit (NCU)	$f_{21}(z) = z - z^3$	Yes	Yes	No	$(-\infty, \infty)$
$z^2 \cos(z)$	$f_{22} = z^2 \cos(z)$	Yes	Yes	No	[,∞)
Shifted Sinc Unit (SSU)	$\pi \operatorname{sinc}(z - \pi)$	Yes	Yes	No	$[-0.68, \pi]$
Growing Cosine Unit (GCU)	$f_{26}(z) = z \cos(z)$	Yes	Yes	No	$(-\infty, \infty)$
Decaying Sine Unit (DSU)	$f_{27}(z) = \frac{\pi}{2}(\operatorname{sinc}(z - \pi) - \operatorname{sinc}(z + \pi))$	Yes	Yes	No	[-1.04, 1.04]

In prior work [12], certain Oscillatory activation functions are shown to possess the following advantages:

- Alleviate the vanishing gradient problem. These functions have non-zero derivatives throughout their domain except at isolated points.
- Improved performance for compact network architectures.
- Computationally cheaper than the state-of-the-art Swish and Mish activation functions [11].

3 Retinal Fundus Multi-disease Image (RFMiD) Dataset

RFMiD dataset is one of IEEE challenges dataset, for multi-disease problem, and has been less prominently used as a research dataset. Having more than 46 labels for diverse eye conditions, very rare eye diseases are also marked and recorded in these images. The variety of diseases ensures label imbalance in the observations and thus demands appropriate augmentation techniques. Clahe (Figure 1), Contrast Stretching (Figure 2), Gamma Correction (Figure 3), Histogram Equilization along with some common augmentations like resize, zoom, brightness, horizontal flip etc. were used. Label weights are also used while training on this dataset to further counter the effects of bloated metrics scores.

Figure 1: Clahe

Figure 2: Contrast Stretching

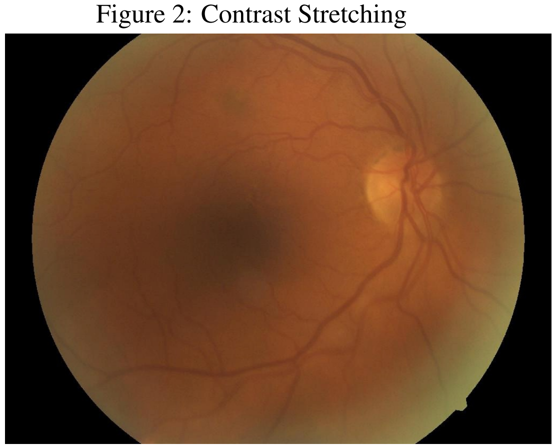

Figure 3: Gamma Correction

We have also chosen Diabetic retiopathy dataset[1] as secondary data, which is a multi-class problem for a particular set of diabetic retinopathy diseases. This is an open source dataset and is readily used for validation purposes. Class weights have also been used for this dataset for better understanding of metrics. Results are fetched for both augmented (same augmentation procedure as above) and non-augmented datasets.

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
1	Mish	SeLU	1.31	88.74%
2	PReLU	Softsign	1.12	88.68%
3	GeLU	SeLU	1.33	88.66%
4	Mish	Growing Cosine Unit (GCU)	1.16	88.46%
5	Softsign	Growing Cosine Unit (GCU)	1.13	88.39%
6	ReLU	Growing Cosine Unit (GCU)	1.12	88.30%
7	Non-Monotonic Cubic	TanH	1.40	88.24%
8	LeakyReLU	Growing Cosine Unit (GCU)	1.17	88.12%
9	Swish	Growing Cosine Unit (GCU)	1.14	88.04%
10	TanH	Growing Cosine Unit (GCU)	1.16	88.03%
11	GeLU	Growing Cosine Unit (GCU)	1.15	88.02%
12	Softplus	TanH	1.23	87.83%
13	TanH	LiSHT	1.13	87.80%
14	PReLU	Growing Cosine Unit (GCU)	1.17	87.68%
15	Softsign	Absolute	1.16	87.67%
16	Non-Monotonic Cubic	SeLU	1.31	87.66%
17	Sigmoid Sine	Growing Cosine Unit (GCU)	1.14	87.64%
18	Non-Monotonic Cubic	Growing Cosine Unit (GCU)	1.14	87.51%
19	Sigmoid	SeLU	1.49	87.40%
20	PReLU	SeLU	1.27	87.30%
21	Swish	eLU	1.35	87.29%
22	TanH	SeLU	1.29	87.28%
23	Sigmoid Sine	TanH	1.21	87.23%
24	LeakyReLU	SeLU	1.15	87.10%
25	Softplus	LiSHT	1.14	87.08%
26	GeLU	Softsign	1.21	87.02%
27	Non-Monotonic Cubic	LiSHT	1.56	86.92%
28	Identity	Growing Cosine Unit (GCU)	1.19	86.92%
29	Sine	eLU	1.47	86.87%
30	ReLU	Absolute	1.26	86.86%
31	Shifted Quadratic Unit	Shifted Quadratic Unit	1.63	86.74%
32	GeLU	LeakyReLU	1.13	86.73%
33	Growing Cosine Unit (GCU)	eLU	1.41	86.59%
34	Bipolar	Growing Cosine Unit (GCU)	1.22	86.48%
35	Identity	SeLU	1.29	86.39%
36	ReLU	eLU	1.36	86.37%
37	Bipolar	eLU	1.29	86.24%
38	Sine	TanH	1.37	86.24%
39	Softplus	eLU	1.43	86.23%
40	Non-Monotonic Cubic	Mish	1.46	86.17%
41	Mish	eLU	1.50	86.17%
42	Swish	Softsign	1.38	86.01%
43	Identity	LeakyReLU	1.25	85.91%
44	Shifted Quadratic Unit	Growing Cosine Unit (GCU)	7.01	85.74%
45	Bipolar	PReLU	1.49	85.65%
46	Sigmoid	Growing Cosine Unit (GCU)	1.23	85.60%
47	Mish	Identity	1.15	85.58%
48	Bipolar	LiSHT	1.25	85.44%
49	Sigmoid	TanH	1.23	85.43%
50	eLU	eLU	1.29	85.39%

4 Trail Setup

5 Results and Discussion

6 Conclusion and Future Work

Experiments around Neural Activation Search (NAS) for oscillatory activation functions in medical domain could suggest more compatible activation functions, over and above those already proposed.

A benchmark for reliability of activation function in a particular architecture can be built, as accuracy and loss are more of performance metrics than the reliability ones.

Reliability metrics could be weighted in nature and could include time/memory optimization metrics, ease of gradient flow, whether some of the redundant neurons/layers could be removed by using a more advanced activation function, like oscillating activation functions via runtime recommendation framework, adaptive learning rate variants of oscillating activation functions could be explored.

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7 Appendix

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
1	Mish	SeLU	1.31	88.74%
2	PReLU	Softsign	1.12	88.68%
3	GeLU	SeLU	1.33	88.66%
4	Mish	Growing Cosine Unit (GCU)	1.16	88.46%
5	Softsign	Growing Cosine Unit (GCU)	1.13	88.39%
6	ReLU	Growing Cosine Unit (GCU)	1.12	88.30%
7	Non-Monotonic Cubic	TanH	1.40	88.24%
8	LeakyReLU	Growing Cosine Unit (GCU)	1.17	88.12%
9	Swish	Growing Cosine Unit (GCU)	1.14	88.04%
10	TanH	Growing Cosine Unit (GCU)	1.16	88.03%
11	GeLU	Growing Cosine Unit (GCU)	1.15	88.02%
12	Softplus	TanH	1.23	87.83%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
13	TanH	LiSHT	1.13	87.80%
14	PReLU	Growing Cosine Unit (GCU)	1.17	87.68%
15	Softsign	Absolute	1.16	87.67%
16	Non-Monotonic Cubic	SeLU	1.31	87.66%
17	Sigmoid Sine	Growing Cosine Unit (GCU)	1.14	87.64%
18	Non-Monotonic Cubic	Growing Cosine Unit (GCU)	1.14	87.51%
19	Sigmoid	SeLU	1.49	87.40%
20	PReLU	SeLU	1.27	87.30%
21	Swish	eLU	1.35	87.29%
22	TanH	SeLU	1.29	87.28%
23	Sigmoid Sine	TanH	1.21	87.23%
24	LeakyReLU	SeLU	1.15	87.10%
25	Softplus	LiSHT	1.14	87.08%
26	GeLU	Softsign	1.21	87.02%
27	Non-Monotonic Cubic	LiSHT	1.56	86.92%
28	Identity	Growing Cosine Unit (GCU)	1.19	86.92%
29	Sine	eLU	1.47	86.87%
30	ReLU	Absolute	1.26	86.86%
31	Shifted Quadratic Unit	Shifted Quadratic Unit	1.63	86.74%
32	GeLU	LeakyReLU	1.13	86.73%
33	Growing Cosine Unit (GCU)	eLU	1.41	86.59%
34	Bipolar	Growing Cosine Unit (GCU)	1.22	86.48%
35	Identity	SeLU	1.29	86.39%
36	ReLU	eLU	1.36	86.37%
37	Bipolar	eLU	1.29	86.24%
38	Sine	TanH	1.37	86.24%
39	Softplus	eLU	1.43	86.23%
40	Non-Monotonic Cubic	Mish	1.46	86.17%
41	Mish	eLU	1.50	86.17%
42	Swish	Softsign	1.38	86.01%
43	Identity	LeakyReLU	1.25	85.91%
44	Shifted Quadratic Unit	Growing Cosine Unit (GCU)	7.01	85.74%
45	Bipolar	PReLU	1.49	85.65%
46	Sigmoid	Growing Cosine Unit (GCU)	1.23	85.60%
47	Mish	Identity	1.15	85.58%
48	Bipolar	LiSHT	1.25	85.44%
49	Sigmoid	TanH	1.23	85.43%
50	eLU	eLU	1.29	85.39%
51	Growing Cosine Unit (GCU)	SeLU	1.16	85.09%
52	LeakyReLU	Sigmoid	1.36	85.03%
53	eLU	Growing Cosine Unit (GCU)	1.27	84.88%
54	Non-Monotonic Cubic	Sine	1.58	84.79%
55	Mish	PReLU	1.38	84.79%
56	Softsign	TanH	1.33	84.68%
57	Identity	eLU	1.29	84.50%
58	Monotonic Cubic	LeakyReLU	12.00	84.46%
59	ReLU	PReLU	1.30	84.44%
60	Softsign	Softsign	1.39	84.29%
61	SeLU	Growing Cosine Unit (GCU)	1.25	84.29%
62	Mish	Softsign	1.34	84.04%
63	Softplus	Growing Cosine Unit (GCU)	1.31	84.02%
64	SeLU	Sigmoid	1.36	83.95%
65	Sigmoid	PReLU	1.45	83.92%
66	Identity	PReLU	1.41	83.88%
67	PReLU	Sigmoid Sine	1.31	83.82%
68	Growing Cosine Unit (GCU)	Growing Cosine Unit (GCU)	1.28	83.73%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
69	Sigmoid Sine	Swish	1.60	83.57%
70	Identity	Softplus	1.60	83.56%
71	Softsign	eLU	1.53	83.51%
72	PReLU	Monotonic Cubic	1.26	83.46%
73	GeLU	ReLU	1.60	83.34%
74	eLU	Mish	1.61	83.32%
75	SeLU	Mish	1.60	83.28%
76	SeLU	Softsign	1.33	83.26%
77	GeLU	TanH	1.25	83.25%
78	Swish	Absolute	1.27	83.21%
79	TanH	Mish	1.60	83.18%
80	Shifted Quadratic Unit	Swish	6.59	83.16%
81	Sine	SeLU	1.48	83.12%
82	SiLU	SeLU	1.16	83.11%
83	GeLU	GeLU	1.60	83.03%
84	ReLU	SeLU	1.31	83.01%
85	Identity	TanH	1.29	82.87%
86	LeakyReLU	Shifted Quadratic Unit	1.30	82.84%
87	ReLU	Mish	1.60	82.83%
88	GeLU	Identity	1.29	82.63%
89	TanH	Sigmoid	1.41	82.53%
90	eLU	SeLU	1.28	82.43%
91	Mish	Sigmoid	1.35	82.35%
92	Identity	Shifted Quadratic Unit	1.33	82.22%
93	PReLU	Absolute	1.38	82.08%
94	Growing Cosine Unit (GCU)	Shifted Quadratic Unit	1.41	81.98%
95	TanH	Swish	1.61	81.94%
96	eLU	PReLU	1.48	81.32%
97	z^2 cos(z)	PReLU	1.57	81.29%
98	LiSHT	Sigmoid	1.36	81.25%
99	Swish	Sigmoid	1.49	81.18%
100	Sine	Growing Cosine Unit (GCU)	1.32	81.15%
101	Shifted Quadratic Unit	Sigmoid	1.50	81.13%
102	Growing Cosine Unit (GCU)	TanH	1.37	81.07%
103	Growing Cosine Unit (GCU)	GeLU	1.60	80.99%
104	Bipolar	Softplus	1.51	80.98%
105	Growing Cosine Unit (GCU)	Mish	1.60	80.98%
106	Sine	Softsign	1.49	80.82%
107	GeLU	eLU	1.36	79.93%
108	Sine	Swish	1.60	79.88%
109	Absolute	LiSHT	1.35	79.85%
110	Absolute	PReLU	1.47	79.73%
111	SeLU	TanH	1.46	79.60%
112	PReLU	LeakyReLU	1.37	79.58%
113	Growing Cosine Unit (GCU)	PReLU	1.40	79.44%
114	SeLU	LeakyReLU	1.35	79.23%
115	z^2 cos(z)	ReLU	1.61	79.13%
116	ReLU	Softsign	1.42	79.09%
117	Swish	PReLU	1.44	78.88%
118	Identity	Identity	1.37	78.86%
119	ReLU	Sigmoid	1.38	78.84%
120	Sine	LiSHT	1.37	78.65%
121	Sigmoid	LeakyReLU	1.34	78.61%
122	Sigmoid Sine	eLU	1.48	78.40%
123	Swish	LiSHT	1.41	78.32%
124	GeLU	Absolute	1.35	78.19%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
125	TanH	eLU	1.36	78.17%
126	z^2 cos(z)	Sigmoid	1.49	78.09%
127	Sine	Shifted Sinc Unit	1.60	78.08%
128	LiSHT	Shifted Quadratic Unit	1.38	78.07%
129	Softplus	Softsign	1.41	78.03%
130	Absolute	Non-Monotonic Cubic	1.36	77.97%
131	Softsign	Sigmoid Sine	1.44	77.90%
132	Swish	Swish	1.58	77.80%
133	Sigmoid Sine	Absolute	1.42	77.74%
134	Shifted Quadratic Unit	Sine	1.41	77.74%
135	LiSHT	SeLU	1.45	77.73%
136	Monotonic Cubic	Sigmoid	1.53	77.70%
137	Bipolar	Absolute	1.47	77.58%
138	LeakyReLU	Identity	1.50	77.51%
139	PReLU	PReLU	1.35	77.47%
140	Sine	Absolute	1.40	77.45%
141	SeLU	Absolute	1.56	77.37%
142	Identity	Softsign	1.37	77.36%
143	LiSHT	PReLU	1.41	77.36%
144	Mish	TanH	1.34	77.24%
145	GeLU	Swish	1.60	77.24%
146	Softplus	Sigmoid	1.47	77.22%
147	LiSHT	Non-Monotonic Cubic	1.39	77.00%
148	ReLU	LeakyReLU	1.38	76.86%
149	TanH	LeakyReLU	1.50	76.64%
150	Mish	Absolute	1.38	76.54%
151	Softsign	Identity	1.43	76.54%
152	Sigmoid	LiSHT	1.35	76.53%
153	TanH	TanH	1.41	76.37%
154	TanH	Identity	1.40	76.33%
155	TanH	Absolute	1.41	76.29%
156	eLU	LiSHT	1.38	76.18%
157	Bipolar	Softsign	1.43	76.09%
158	Softplus	Absolute	1.42	76.05%
159	Mish	LiSHT	1.51	75.91%
160	LeakyReLU	PReLU	1.48	75.71%
161	Softsign	Sigmoid	1.43	75.61%
162	GeLU	Monotonic Cubic	1.44	75.60%
163	PReLU	GeLU	1.61	75.57%
164	Mish	Shifted Quadratic Unit	1.39	75.53%
165	Identity	Non-Monotonic Cubic	1.41	75.43%
166	LeakyReLU	TanH	1.41	75.41%
167	Growing Cosine Unit (GCU)	Decaying Sine Unit (DSU)	1.60	75.39%
168	Non-Monotonic Cubic	Sigmoid	1.59	75.28%
169	Identity	Sigmoid	1.40	75.25%
170	Identity	Mish	1.60	75.19%
171	Identity	GeLU	1.60	75.15%
172	TanH	Shifted Quadratic Unit	1.47	74.94%
173	ReLU	LiSHT	1.47	74.89%
174	eLU	Non-Monotonic Cubic	1.47	74.86%
175	Sine	Mish	1.60	74.83%
176	Swish	TanH	1.51	74.80%
177	Identity	Absolute	1.40	74.80%
178	Shifted Quadratic Unit	Sigmoid Sine	1.46	74.79%
179	Growing Cosine Unit (GCU)	Softplus	1.60	74.76%
180	eLU	Softsign	1.43	74.69%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
181	SeLU	Identity	1.46	74.66%
182	eLU	Sigmoid	1.45	74.56%
183	Bipolar	LeakyReLU	1.41	74.52%
184	Absolute	eLU	1.45	74.47%
185	Shifted Quadratic Unit	Decaying Sine Unit (DSU)	1.58	74.44%
186	PReLU	Identity	1.42	74.31%
187	Sigmoid Sine	Monotonic Cubic	1.47	74.22%
188	Softsign	LiSHT	1.43	74.17%
189	LeakyReLU	LeakyReLU	1.44	74.10%
190	Mish	Non-Monotonic Cubic	1.44	74.06%
191	SeLU	SeLU	1.31	74.05%
192	Non-Monotonic Cubic	Softsign	1.49	73.99%
193	Sigmoid	Softsign	1.47	73.97%
194	Sine	LeakyReLU	1.46	73.91%
195	TanH	Sigmoid Sine	1.45	73.91%
196	Sine	Decaying Sine Unit (DSU)	1.60	73.87%
197	TanH	Monotonic Cubic	1.44	73.66%
198	Growing Cosine Unit (GCU)	Softsign	1.51	73.64%
199	Absolute	Absolute	1.44	73.33%
200	SeLU	Sigmoid Sine	1.45	73.30%
201	Mish	LeakyReLU	1.42	73.28%
202	Sigmoid Sine	SeLU	1.37	73.12%
203	Sigmoid	Sigmoid	1.45	73.12%
204	Sigmoid Sine	Decaying Sine Unit (DSU)	1.60	73.10%
205	Sigmoid Sine	GeLU	1.60	73.09%
206	Sigmoid	eLU	1.52	73.08%
207	Non-Monotonic Cubic	LeakyReLU	1.57	73.06%
208	LeakyReLU	LiSHT	1.43	73.06%
209	GeLU	Sigmoid Sine	1.45	73.05%
210	Softplus	PReLU	1.40	73.03%
211	ReLU	Identity	1.42	72.92%
212	Softsign	SeLU	1.52	72.91%
213	PReLU	Sigmoid	1.42	72.81%
214	ReLU	TanH	1.44	72.75%
215	Sine	Identity	1.50	72.72%
216	LiSHT	LeakyReLU	1.48	72.71%
217	Swish	LeakyReLU	1.45	72.70%
218	Softplus	SeLU	1.41	72.66%
219	ReLU	Swish	1.59	72.58%
220	TanH	Softsign	1.48	72.44%
221	z^2 cos(z)	LeakyReLU	1.56	72.27%
222	LiSHT	eLU	1.45	72.21%
223	Absolute	Identity	1.46	72.12%
224	Shifted Quadratic Unit	Softsign	1.54	72.12%
225	SeLU	Monotonic Cubic	1.47	71.91%
226	eLU	Swish	1.40	71.88%
227	Softplus	Monotonic Cubic	1.48	71.73%
228	Mish	Swish	1.49	71.69%
229	LeakyReLU	Sigmoid Sine	1.46	71.65%
230	Softsign	PReLU	1.49	71.57%
231	ReLU	Shifted Quadratic Unit	1.51	71.55%
232	z^2 cos(z)	SeLU	1.57	71.53%
233	ReLU	Non-Monotonic Cubic	1.47	71.43%
234	Sigmoid Sine	LeakyReLU	1.49	71.38%
235	Absolute	TanH	1.47	71.37%
236	eLU	Absolute	1.47	71.36%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
237	Identity	LiSHT	1.48	71.36%
238	Growing Cosine Unit (GCU)	Sigmoid Sine	1.49	71.36%
239	Softsign	Non-Monotonic Cubic	1.49	71.33%
240	Softsign	LeakyReLU	1.47	71.28%
241	Sigmoid Sine	Softsign	1.40	71.16%
242	PReLU	TanH	1.47	71.10%
243	SeLU	LiSHT	1.45	71.08%
244	eLU	Shifted Quadratic Unit	1.48	71.06%
245	Swish	Monotonic Cubic	1.52	71.03%
246	eLU	Identity	1.50	70.93%
247	GeLU	Shifted Quadratic Unit	1.46	70.77%
248	GeLU	Non-Monotonic Cubic	1.47	70.71%
249	Swish	Identity	1.47	70.70%
250	Shifted Quadratic Unit	SeLU	504.64	70.62%
251	SeLU	eLU	1.42	70.62%
252	Identity	Monotonic Cubic	1.51	70.52%
253	Sine	PReLU	1.53	70.42%
254	Softplus	Shifted Quadratic Unit	1.50	70.37%
255	z^2 cos(z)	Shifted Quadratic Unit	6.18	70.32%
256	Growing Cosine Unit (GCU)	Absolute	1.50	70.30%
257	z^2 cos(z)	Sine	1.50	70.30%
258	Swish	Shifted Quadratic Unit	1.48	70.17%
259	ReLU	Sigmoid Sine	1.48	70.13%
260	LiSHT	LiSHT	1.50	70.09%
261	Shifted Quadratic Unit	Shifted Sinc Unit	1.59	70.08%
262	Sigmoid	Absolute	1.48	70.07%
263	SeLU	PReLU	1.50	70.02%
264	LiSHT	Monotonic Cubic	1.49	70.02%
265	Sigmoid	Shifted Quadratic Unit	1.50	69.99%
266	PReLU	Shifted Quadratic Unit	1.52	69.94%
267	eLU	TanH	1.47	69.87%
268	PReLU	LiSHT	1.48	69.87%
269	Absolute	LeakyReLU	1.47	69.79%
270	Sine	Sigmoid	1.44	69.75%
271	Identity	Sigmoid Sine	1.46	69.69%
272	Sigmoid Sine	LiSHT	1.50	69.67%
273	Absolute	Shifted Quadratic Unit	1.51	69.65%
274	GeLU	LiSHT	1.49	69.48%
275	z^2 cos(z)	LiSHT	1.53	69.48%
276	LeakyReLU	Non-Monotonic Cubic	1.51	69.35%
277	Growing Cosine Unit (GCU)	LiSHT	1.51	69.27%
278	Swish	Non-Monotonic Cubic	1.49	69.22%
279	LiSHT	Absolute	1.50	69.21%
280	Softsign	Monotonic Cubic	1.51	69.18%
281	Softplus	LeakyReLU	1.50	69.17%
282	LeakyReLU	Softsign	1.49	69.09%
283	ReLU	Monotonic Cubic	1.50	68.95%
284	Absolute	Softsign	1.51	68.92%
285	Softplus	Non-Monotonic Cubic	1.51	68.89%
286	GeLU	Sigmoid	1.50	68.78%
287	PReLU	Non-Monotonic Cubic	1.50	68.62%
288	Bipolar	Identity	1.52	68.55%
289	Swish	Sigmoid Sine	1.51	68.46%
290	LiSHT	Identity	1.49	68.40%
291	Softsign	Decaying Sine Unit (DSU)	1.60	68.38%
292	Softsign	Shifted Quadratic Unit	1.49	68.13%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
293	Bipolar	Non-Monotonic Cubic	1.52	68.11%
294	eLU	LeakyReLU	1.49	68.08%
295	GeLU	PReLU	1.52	67.63%
296	Bipolar	Sigmoid	1.51	67.56%
297	Growing Cosine Unit (GCU)	Non-Monotonic Cubic	1.54	67.55%
298	SeLU	Non-Monotonic Cubic	1.51	67.52%
299	TanH	PReLU	1.53	67.45%
300	Bipolar	Shifted Quadratic Unit	1.52	67.42%
301	eLU	Monotonic Cubic	1.52	67.40%
302	Absolute	Sigmoid	1.52	67.38%
303	Sine	Shifted Quadratic Unit	1.55	66.87%
304	LeakyReLU	Absolute	1.51	66.76%
305	Sigmoid	Identity	1.52	66.73%
306	LeakyReLU	Monotonic Cubic	1.52	66.70%
307	eLU	Sigmoid Sine	1.51	66.64%
308	Non-Monotonic Cubic	Identity	1.54	66.51%
309	Sigmoid Sine	Identity	1.54	66.50%
310	Sigmoid	Sigmoid Sine	1.53	66.48%
311	z^2 cos(z)	TanH	1.56	66.46%
312	Bipolar	Monotonic Cubic	1.54	66.43%
313	Growing Cosine Unit (GCU)	Sigmoid	1.44	66.26%
314	Sigmoid Sine	Non-Monotonic Cubic	1.54	66.15%
315	Absolute	SeLU	1.55	66.11%
316	Sigmoid	Monotonic Cubic	1.54	66.11%
317	Sigmoid Sine	Shifted Quadratic Unit	1.55	66.11%
318	Non-Monotonic Cubic	Absolute	1.61	66.02%
319	Shifted Quadratic Unit	LeakyReLU	8.24	65.94%
320	Sine	Non-Monotonic Cubic	1.54	65.72%
321	Mish	Monotonic Cubic	1.52	65.70%
322	z^2 cos(z)	Sigmoid Sine	1.53	65.55%
323	Absolute	Sigmoid Sine	1.54	65.49%
324	LiSHT	Growing Cosine Unit (GCU)	4.07	65.49%
325	Sigmoid	Non-Monotonic Cubic	1.55	65.37%
326	Sigmoid Sine	PReLU	1.54	65.20%
327	Swish	SeLU	1.50	65.06%
328	LiSHT	Sigmoid Sine	1.55	64.62%
329	Softplus	Identity	1.54	64.53%
330	Bipolar	Sigmoid Sine	1.55	64.51%
331	Mish	Sigmoid Sine	1.54	64.50%
332	LiSHT	TanH	1.56	64.21%
333	SiLU	eLU	1.43	64.20%
334	PReLU	eLU	1.43	64.13%
335	Sigmoid Sine	Sigmoid	1.43	64.10%
336	Monotonic Cubic	TanH	1.60	63.85%
337	z^2 cos(z)	Decaying Sine Unit (DSU)	1.58	63.62%
338	z^2 cos(z)	Identity	1.60	63.58%
339	TanH	Non-Monotonic Cubic	1.54	63.35%
340	LeakyReLU	eLU	1.38	63.07%
341	Shifted Quadratic Unit	TanH	1.55	62.81%
342	Sine	Sigmoid Sine	1.50	62.77%
343	SeLU	Shifted Quadratic Unit	1.55	62.66%
344	Sigmoid Sine	Sigmoid Sine	1.57	62.43%
345	Growing Cosine Unit (GCU)	LeakyReLU	1.55	62.18%
346	SeLU	GeLU	1.56	61.08%
347	LiSHT	Softsign	1.57	60.70%
348	Softplus	Sigmoid Sine	1.58	60.44%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
349	z^2 cos(z)	Shifted Sinc Unit	1.58	60.22%
350	SiLU	Swish	1.59	60.10%
351	Absolute	Monotonic Cubic	1.62	59.70%
352	z^2 cos(z)	Softsign	1.57	59.39%
353	Sine	Monotonic Cubic	1.58	59.39%
354	TanH	Decaying Sine Unit (DSU)	1.61	59.36%
355	Absolute	Softplus	1.63	58.55%
356	Softplus	Shifted Sinc Unit	1.58	58.54%
357	Growing Cosine Unit (GCU)	Monotonic Cubic	7.57	58.08%
358	PReLU	Mish	1.56	58.05%
359	Sigmoid Sine	Shifted Sinc Unit	1.60	57.79%
360	SeLU	Decaying Sine Unit (DSU)	1.60	57.66%
361	Identity	Decaying Sine Unit (DSU)	1.60	57.61%
362	Bipolar	Decaying Sine Unit (DSU)	1.61	57.51%
363	z^2 cos(z)	Absolute	1.58	57.45%
364	Swish	Shifted Sinc Unit	1.58	57.32%
365	GeLU	Mish	1.59	57.23%
366	LeakyReLU	Decaying Sine Unit (DSU)	1.60	57.22%
367	LeakyReLU	Mish	1.60	57.22%
368	Non-Monotonic Cubic	PReLU	1.59	56.75%
369	Softplus	Decaying Sine Unit (DSU)	1.60	56.51%
370	GeLU	Decaying Sine Unit (DSU)	1.61	56.36%
371	LeakyReLU	Shifted Sinc Unit	1.58	56.12%
372	Non-Monotonic Cubic	Shifted Sinc Unit	1.59	56.05%
373	z^2 cos(z)	eLU	1.60	55.72%
374	Identity	ReLU	1.59	55.72%
375	Monotonic Cubic	LiSHT	1724.11	55.52%
376	Swish	Sine	1.60	55.10%
377	eLU	Softplus	1.59	55.03%
378	Sine	Sine	1.60	54.91%
379	Softplus	Sine	1.61	54.82%
380	Mish	Sine	1.61	54.58%
381	eLU	Shifted Sinc Unit	1.61	54.47%
382	eLU	ReLU	1.60	54.35%
383	Growing Cosine Unit (GCU)	Sine	1.60	54.30%
384	LiSHT	Sine	1.60	54.13%
385	PReLU	Sine	1.61	54.07%
386	Sigmoid Sine	Sine	1.61	54.05%
387	Softsign	Sine	1.61	53.99%
388	LeakyReLU	Sine	1.61	53.82%
389	SeLU	Sine	1.61	53.81%
390	ReLU	Sine	1.61	53.70%
391	Sigmoid	Sine	1.61	53.62%
392	TanH	Sine	1.61	53.45%
393	GeLU	Sine	1.61	53.42%
394	Absolute	Decaying Sine Unit (DSU)	1.61	53.29%
395	Identity	Sine	1.62	53.17%
396	Growing Cosine Unit (GCU)	Identity	1.60	53.14%
397	Absolute	Sine	1.61	53.02%
398	Absolute	Mish	1.56	52.76%
399	ReLU	ReLU	1.60	52.33%
400	eLU	Sine	1.62	52.01%
401	Sigmoid	GeLU	1.61	51.99%
402	Bipolar	Mish	1.59	51.76%
403	Sigmoid	Swish	1.61	51.72%
404	Swish	Decaying Sine Unit (DSU)	1.61	51.63%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
405	Softplus	Mish	1.60	51.19%
406	Absolute	Shifted Sinc Unit	1.61	51.17%
407	eLU	Decaying Sine Unit (DSU)	1.61	51.00%
408	SeLU	ReLU	1.58	50.87%
409	ReLU	Shifted Sinc Unit	1.60	50.57%
410	ReLU	Decaying Sine Unit (DSU)	1.61	50.53%
411	LiSHT	Softplus	1.61	50.33%
412	LeakyReLU	Swish	1.61	50.30%
413	LiSHT	Mish	1.62	50.28%
414	Non-Monotonic Cubic	Softplus	137395344.00	50.26%
415	Swish	Softplus	1.61	50.25%
416	Non-Monotonic Cubic	GeLU	5097472917504.00	50.22%
417	PReLU	ReLU	1.61	50.09%
418	SeLU	Swish	1.61	50.07%
419	Sigmoid	Shifted Sinc Unit	1.60	50.06%
420	Growing Cosine Unit (GCU)	ReLU	1.61	50.05%
421	SiLU	ReLU	1.61	50.02%
422	Shifted Quadratic Unit	ReLU	858.93	50.02%
423	Shifted Quadratic Unit	GeLU	4.87	50.01%
424	LeakyReLU	GeLU	1.61	50.00%
425	Softplus	ReLU	1.61	50.00%
426	Softplus	GeLU	1.61	50.00%
427	Softsign	ReLU	1.61	50.00%
428	Softsign	Mish	1.61	50.00%
429	ReLU	GeLU	1.61	50.00%
430	GeLU	Softplus	1.61	50.00%
431	TanH	GeLU	1.61	50.00%
432	Sine	Softplus	1.61	50.00%
433	z^2 cos(z)	Softplus	1.61	50.00%
434	Sigmoid Sine	Softplus	1.61	50.00%
435	Sigmoid Sine	Mish	1.61	50.00%
436	Swish	ReLU	1.61	49.98%
437	LiSHT	Shifted Sinc Unit	1.62	49.97%
438	z^2 cos(z)	GeLU	1.65	49.97%
439	Mish	Softplus	1.61	49.95%
440	Bipolar	Swish	1.61	49.95%
441	Swish	GeLU	1.57	49.72%
442	ReLU	Softplus	1.61	49.51%
443	Shifted Quadratic Unit	Absolute	2.15	49.47%
444	Absolute	Growing Cosine Unit (GCU)	109.98	49.21%
445	Absolute	z^2 cos(z)	849842.88	49.02%
446	z^2 cos(z)	Non-Monotonic Cubic	28789.98	48.22%
447	Mish	Shifted Sinc Unit	1.61	48.21%
448	LeakyReLU	z^2 cos(z)	57826.47	48.12%
449	Softsign	z^2 cos(z)	1370.85	48.08%
450	SeLU	Shifted Sinc Unit	1.61	48.07%
451	Sigmoid	ReLU	1.59	48.03%
452	ReLU	z^2 cos(z)	539.18	47.70%
453	Sigmoid	z^2 cos(z)	5782.32	47.67%
454	SeLU	z^2 cos(z)	1540.46	47.60%
455	Sigmoid Sine	ReLU	1.59	47.56%
456	LiSHT	z^2 cos(z)	239077.69	47.38%
457	Growing Cosine Unit (GCU)	z^2 cos(z)	8905.09	47.38%
458	Absolute	GeLU	1.60	47.36%
459	GeLU	z^2 cos(z)	104686.34	47.34%
460	Mish	z^2 cos(z)	120978.38	47.34%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
461	PReLU	z^2 cos(z)	4185.62	47.29%
462	Sigmoid	Mish	1.61	47.28%
463	Identity	z^2 cos(z)	8379.08	47.27%
464	Sine	ReLU	1.61	47.14%
465	TanH	z^2 cos(z)	1713.46	47.03%
466	Sigmoid Sine	z^2 cos(z)	1205.20	47.02%
467	Identity	Shifted Sinc Unit	1.61	46.89%
468	Softplus	z^2 cos(z)	3264.78	46.84%
469	Sine	z^2 cos(z)	4872.96	46.77%
470	LeakyReLU	Softplus	1.61	46.69%
471	z^2 cos(z)	z^2 cos(z)	215972.95	46.67%
472	Bipolar	GeLU	1.60	46.32%
473	Swish	z^2 cos(z)	5745.46	46.27%
474	eLU	z^2 cos(z)	7076.36	45.73%
475	LiSHT	GeLU	1.62	45.33%
476	Growing Cosine Unit (GCU)	Shifted Sinc Unit	1.61	44.77%
477	LiSHT	Swish	1.61	43.87%
478	Shifted Quadratic Unit	eLU	3.64	43.70%
479	TanH	Shifted Sinc Unit	1.61	43.19%
480	z^2 cos(z)	Monotonic Cubic	2232.36	42.81%
481	LiSHT	ReLU	1.59	42.66%
482	Mish	Mish	1.60	42.54%
483	z^2 cos(z)	Swish	1.61	42.52%
484	SeLU	Softplus	1.61	42.48%
485	Softplus	Swish	1.61	42.36%
486	LeakyReLU	ReLU	1.61	42.34%
487	Softplus	Softplus	1.61	42.30%
488	Shifted Quadratic Unit	Monotonic Cubic	3.66	42.23%
489	Absolute	ReLU	1.61	41.36%
490	Absolute	Swish	1.61	41.06%
491	Softsign	Swish	1.61	40.76%
492	Shifted Quadratic Unit	Identity	11.55	40.33%
493	Sine	GeLU	1.61	39.42%
494	Softsign	Shifted Sinc Unit	1.61	39.34%
495	Identity	Swish	1.61	39.29%
496	Shifted Quadratic Unit	z^2 cos(z)	530497.81	39.13%
497	Monotonic Cubic	Mish	1.62	39.07%
498	TanH	ReLU	1.61	39.02%
499	Non-Monotonic Cubic	Swish	1.65	38.98%
500	TanH	Softplus	1.61	38.94%
501	Growing Cosine Unit (GCU)	Swish	1.61	38.92%
502	Mish	ReLU	1.61	38.80%
503	Softsign	Softplus	1.61	38.75%
504	Mish	GeLU	1.61	38.74%
505	Softsign	GeLU	1.61	38.72%
506	Non-Monotonic Cubic	ReLU	116071.99	38.62%
507	eLU	GeLU	1.60	37.65%
508	Swish	Mish	1.64	37.46%
509	z^2 cos(z)	Growing Cosine Unit (GCU)	2.93	35.84%
510	Shifted Quadratic Unit	LiSHT	15.64	35.77%
511	Shifted Quadratic Unit	Non-Monotonic Cubic	1553881.38	34.70%
512	Sigmoid	Softplus	1.59	34.19%
513	PReLU	Softplus	1.58	32.67%
514	z^2 cos(z)	Mish	1.61	31.43%
515	Shifted Quadratic Unit	Softplus	1.96	29.25%
516	PReLU	Swish	1.61	28.70%

Index	Activation Function	Dense Activation Function	Test Loss	Test AUC
517	Non-Monotonic Cubic	eLU	136328.61	26.30%
518	Shifted Quadratic Unit	Mish	29.73	15.41%
519	Shifted Quadratic Unit	PReLU	1.90	15.29%
520	Monotonic Cubic	SeLU	23.79	14.94%

Table 2: Master table for test results on non-augmented Diabetic Retinopathy Dataset with VGG Network having combinations of activation functions as hyperparameter

Index	Monotonic Cubic	Dense Activation Function
0	LeakyReLU	Bipolar
1	LeakyReLU	SiLU
2	PReLU	Bipolar
3	PReLU	SiLU
4	PReLU	Shifted Sinc Unit (SSU)
5	PReLU	Decaying Sine Unit (DSU)
6	Sigmoid	Bipolar
7	Sigmoid	SiLU
8	Sigmoid	Decaying Sine Unit (DSU)
9	Softplus	Bipolar
10	Softplus	SiLU
11	Softsign	Bipolar
12	Softsign	SiLU
13	ReLU	Bipolar
14	ReLU	SiLU
15	GeLU	Bipolar
16	GeLU	SiLU
17	GeLU	Shifted Sinc Unit (SSU)
18	SeLU	Bipolar
19	SeLU	SiLU
20	eLU	Bipolar
21	eLU	SiLU
22	TanH	Bipolar
23	TanH	SiLU
24	Absolute	Bipolar
25	Absolute	SiLU
26	Growing Cosine Unit (GCU)	Bipolar
27	Growing Cosine Unit (GCU)	SiLU
28	LiSHT	Bipolar
29	LiSHT	SiLU
30	LiSHT	Decaying Sine Unit (DSU)
31	Sine	Bipolar
32	Sine	SiLU
33	z^2 cos(z)	Bipolar
34	z^2 cos(z)	SiLU
35	Swish	Bipolar
36	Swish	SiLU
37	Mish	Bipolar
38	Mish	SiLU
39	Mish	Decaying Sine Unit (DSU)
40	Sigmoid Sine	Bipolar
41	Sigmoid Sine	SiLU
42	Identity	Bipolar
43	Identity	SiLU
44	Bipolar	ReLU
45	Bipolar	SeLU

Index	Monotonic Cubic	Dense Activation Function
46	Bipolar	TanH
47	Bipolar	Sine
48	Bipolar	z^2 cos(z)
49	Bipolar	Bipolar
50	Bipolar	SiLU
51	Bipolar	Shifted Sinc Unit (SSU)
52	Non-Monotonic Cubic	z^2 cos(z)
53	Non-Monotonic Cubic	Sigmoid Sine
54	Non-Monotonic Cubic	Bipolar
55	Non-Monotonic Cubic	Non-Monotonic Cubic
56	Non-Monotonic Cubic	SiLU
57	Non-Monotonic Cubic	Shifted Quadratic Unit
58	Non-Monotonic Cubic	Decaying Sine Unit (DSU)
59	Non-Monotonic Cubic	Monotonic Cubic
60	SiLU	LeakyReLU
61	SiLU	PReLU
62	SiLU	Sigmoid
63	SiLU	Softplus
64	SiLU	Softsign
65	SiLU	GeLU
66	SiLU	TanH
67	SiLU	Absolute
68	SiLU	Growing Cosine Unit (GCU)
69	SiLU	LiSHT
70	SiLU	Sine
71	SiLU	z^2 cos(z)
72	SiLU	Mish
73	SiLU	Sigmoid Sine
74	SiLU	Identity
75	SiLU	Bipolar
76	SiLU	Non-Monotonic Cubic
77	SiLU	SiLU
78	SiLU	Shifted Quadratic Unit
79	SiLU	Shifted Sinc Unit (SSU)
80	SiLU	Decaying Sine Unit (DSU)
81	SiLU	Monotonic Cubic
82	Shifted Quadratic Unit	Bipolar
83	Shifted Quadratic Unit	SiLU
84	Shifted Sinc Unit (SSU)	LeakyReLU
85	Shifted Sinc Unit (SSU)	PReLU
86	Decaying Sine Unit (DSU)	Mish
87	Decaying Sine Unit (DSU)	Sigmoid Sine
88	Decaying Sine Unit (DSU)	Identity
89	Decaying Sine Unit (DSU)	Bipolar
90	Decaying Sine Unit (DSU)	Non-Monotonic Cubic
91	Decaying Sine Unit (DSU)	SiLU
92	Decaying Sine Unit (DSU)	Shifted Quadratic Unit
93	Decaying Sine Unit (DSU)	Shifted Sinc Unit (SSU)
94	Decaying Sine Unit (DSU)	Decaying Sine Unit (DSU)
95	Decaying Sine Unit (DSU)	Monotonic Cubic
96	Monotonic Cubic	PReLU
97	Monotonic Cubic	Softplus
98	Monotonic Cubic	Softsign
99	Monotonic Cubic	ReLU
100	Monotonic Cubic	GeLU
101	Monotonic Cubic	eLU

Index	Monotonic Cubic	Dense Activation Function
102	Monotonic Cubic	Absolute
103	Monotonic Cubic	Growing Cosine Unit (GCU)
104	Monotonic Cubic	Sine
105	Monotonic Cubic	z^2 cos(z)
106	Monotonic Cubic	Swish
107	Monotonic Cubic	Sigmoid Sine
108	Monotonic Cubic	Identity
109	Monotonic Cubic	Bipolar
110	Monotonic Cubic	Non-Monotonic Cubic
111	Monotonic Cubic	SiLU
112	Monotonic Cubic	Shifted Quadratic Unit
113	Monotonic Cubic	Shifted Sinc Unit (SSU)
114	Monotonic Cubic	Decaying Sine Unit (DSU)
115	Monotonic Cubic	Monotonic Cubic

Table 3: Master table for combinations of activation functions breaking on non-augmented Diabetic Retinopathy Dataset with VGG Network