



# Bimodal Deep Learning Architecture for Malware Classification

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# Presentation Outline:

1. Introduction
2. The Deep Learning Models
  - a. Image Classification Modality
    - CNN A model
  - b. Natural Language Processing Modality
    - CNN B model
    - CNN C model
  - c. Bimodal Architecture
    - Sequential Model
3. Experimental Results & Discussion
4. Conclusion

# Introduction

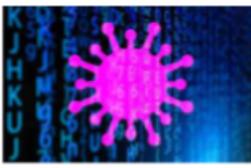
# Introduction: Malware Types



Adware



Spyware



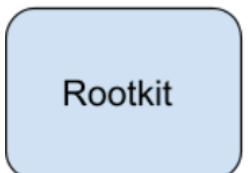
Virus



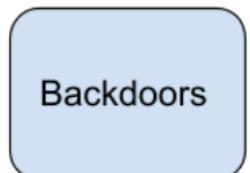
Worm



Trojan



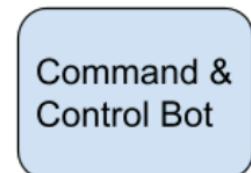
Rootkit



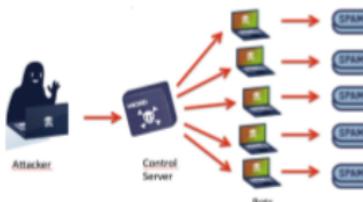
Backdoors



Ransomware

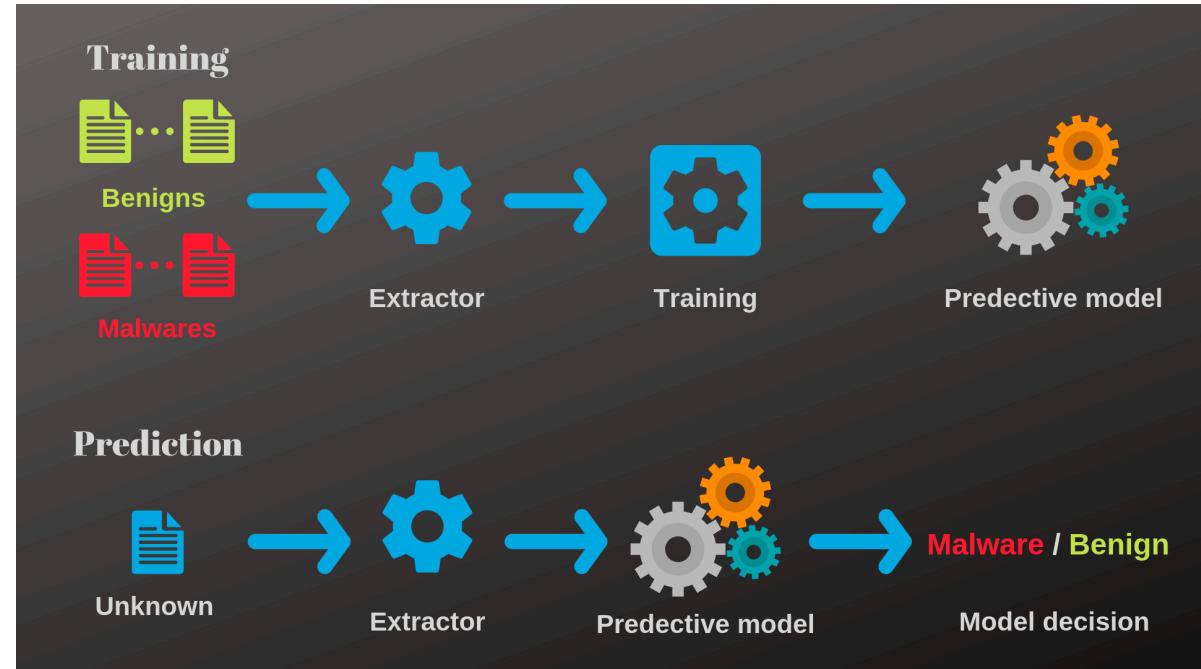


Command &  
Control Bot



# Introduction: Malware Detection and Classification

- Every day 560,000 new pieces of malware are detected.
- Malware develop polymorphic and metamorphic malware to evade detection.
- Conventional detection methods are insufficient to detect malware.
- Traditional antivirus solutions relies on signature-based and heuristic based methods.
- Use of machine learning techniques for malware classification and detection increased in the last years.
- Machine learning feature extraction of malware data;
  1. Static features, 2. Dynamic features



# Introduction: Objective

- The objective of this project is to classify malware samples from BIG2015 dataset into their corresponding malware families.

index	name	# of instance in the dataset	type of malware
1	Ramnit	1541	Worm
2	Lollipop	2478	Adware
3	Kelihos_ver3	2942	Backdoor
4	Vundo	475	Trojan
5	Simda	42	Backdoor
6	Tracur	751	TrojanDownloader
7	Kelihos_ver1	398	Backdoor
8	Obfuscator.AC Y	1228	Obfuscated malware
9	Gatak	1013	Backdoor

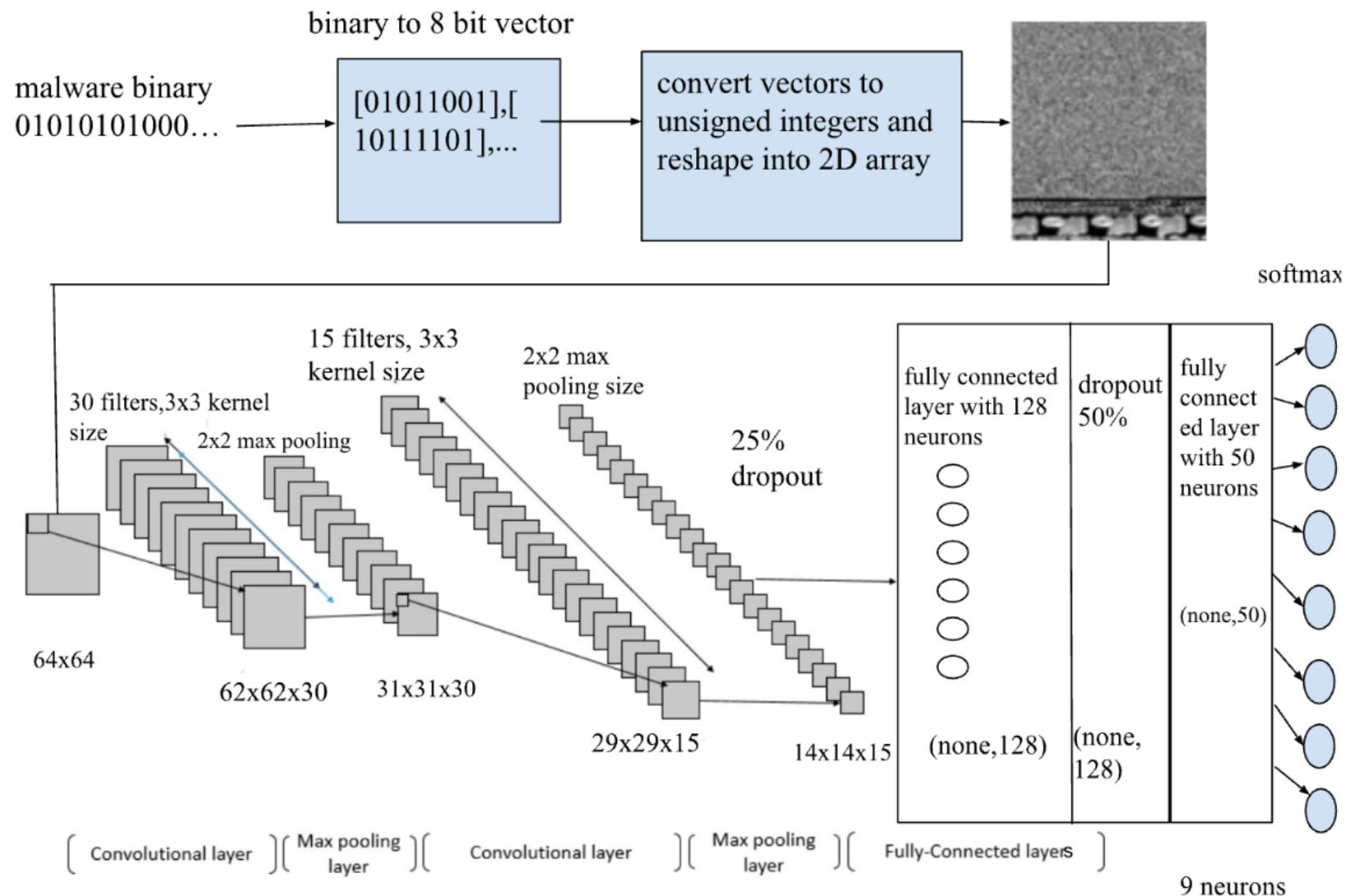
```
00401010 BB 42 00 8B C6 5E C2 04 00 CC CC CC CC CC CC CC  
00401020 C7 01 08 BB 42 00 E9 26 1C 00 00 CC CC CC CC CC  
00401030 56 8B F1 C7 06 08 BB 42 00 E8 13 1C 00 00 F6 44  
00401040 24 08 01 74 09 56 E8 6C 1E 00 00 83 C4 04 8B C6  
00401050 5E C2 04 00 CC  
00401060 8B 44 24 08 8A 08 8B 54 24 04 88 0A C3 CC CC CC  
00401070 8B 44 24 04 8D 50 01 8A 08 40 84 C9 75 F9 2B C2  
00401080 C3 CC  
00401090 8B 44 24 10 8B 4C 24 0C 8B 54 24 08 56 8B 74 24  
004010A0 08 50 51 52 56 E8 18 1E 00 00 83 C4 10 8B C6 5E  
004010B0 C3 CC  
004010C0 8B 44 24 10 8B 4C 24 0C 8B 54 24 08 56 8B 74 24  
004010D0 08 50 51 52 56 E8 65 1E 00 00 83 C4 10 8B C6 5E  
004010E0 C3 CC  
004010F0 33 C0 C2 10 00 CC  
00401100 B8 08 00 00 00 C2 04 00 CC CC CC CC CC CC CC CC
```

```
.text:00401174 ; -----  
.text:00401177 CC align 10h  
.text:00401180 6A 04 push 4  
.text:00401182 68 00 10 00 00 push 1000h  
.text:00401187 68 68 BE 1C 00 push 1CBE68h  
.text:0040118C 6A 00 push 0  
.text:0040118E FF 15 9C 63 52 00 call ds:GetCurrentProcess  
.text:00401194 50 push eax  
.text:00401195 FF 15 C8 63 52 00 call ds:VirtualAllocEx  
.text:0040119B 8B 4C 24 04 mov ecx, [esp+4]  
.text:0040119F 6A 00 push 0  
.text:004011A1 6A 40 push 40h  
.text:004011A3 68 68 BE 1C 00 push 1CBE68h  
.text:004011A8 50 push eax  
.text:004011A9 89 01 mov [ecx], eax  
.text:004011AB FF 15 C4 63 52 00 call ds:VirtualProtect  
.text:004011B1 B8 04 00 00 00 mov eax, 4  
.text:004011B6 C2 04 00 retn 4
```

# The Deep Learning Models:

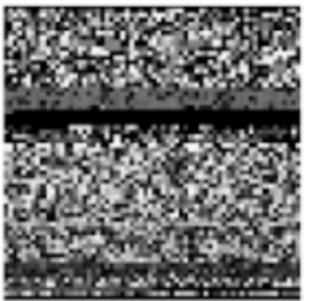
- Image Classification Modality
- Natural Language Processing Modality
- Bimodal Sequential Model

# Models: Image Classification Modality



# Models: Raw Byte File to Grayscale Images

ramnit



ramnit



lollipop



lollipop



vundo



vundo



ramnit



ramnit



lollipop



lollipop



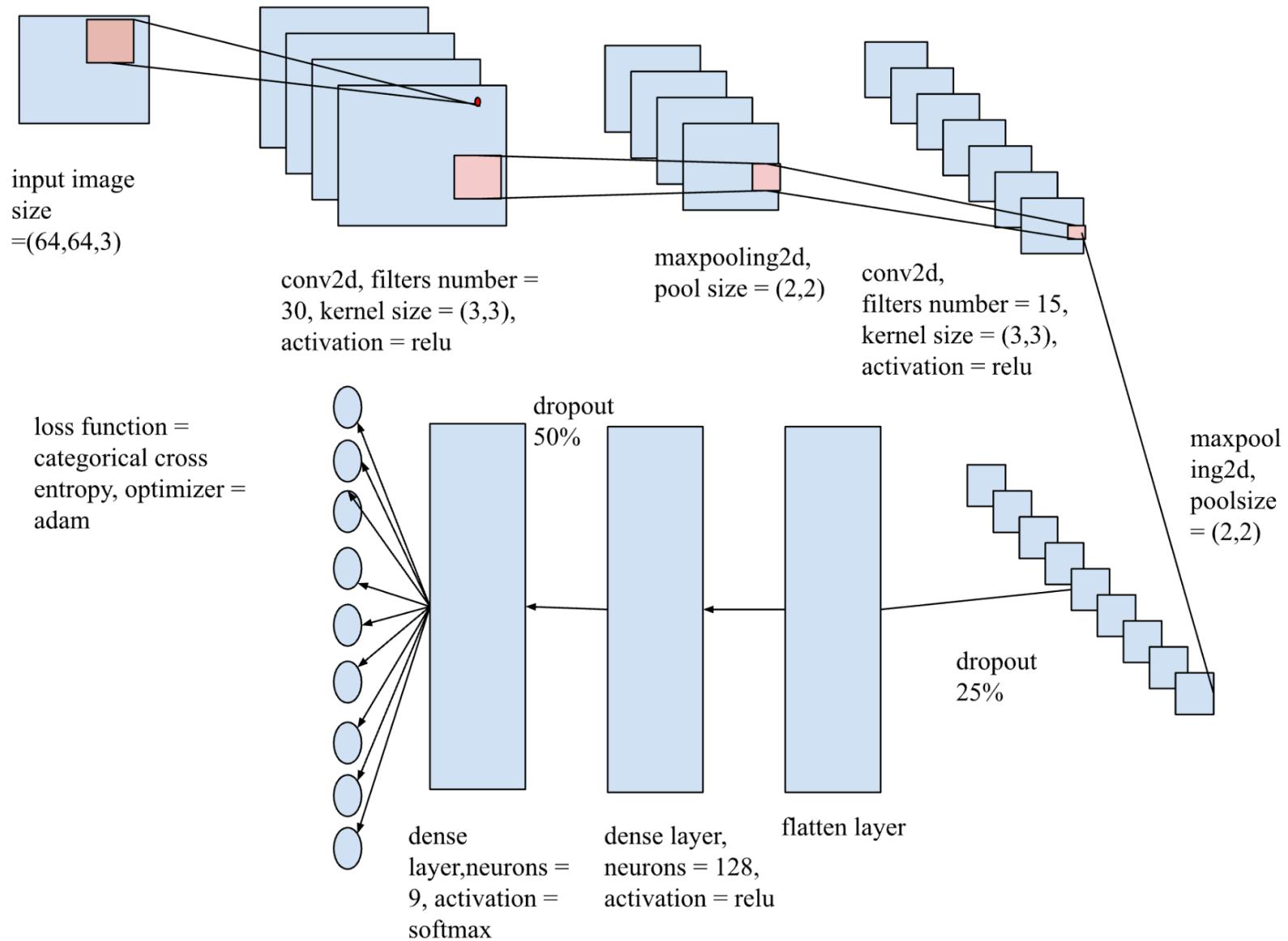
vundo



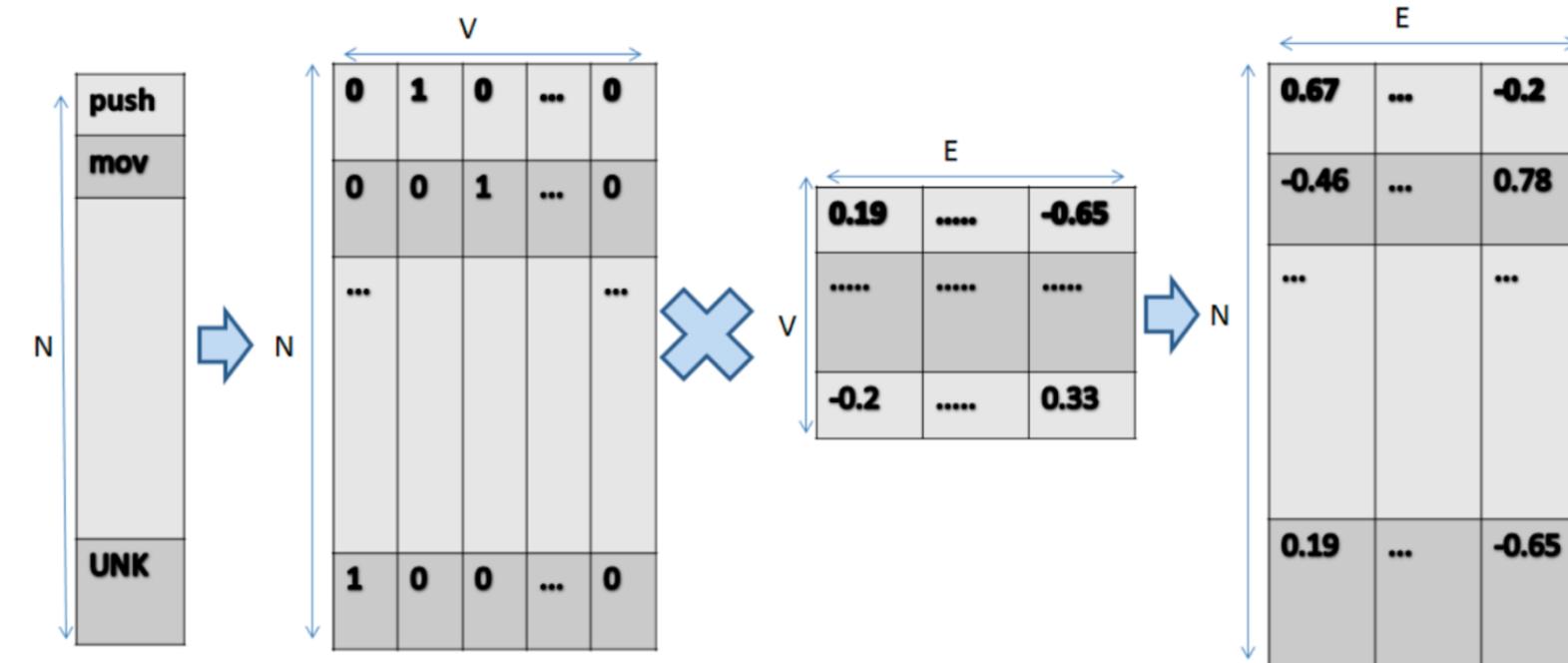
vundo



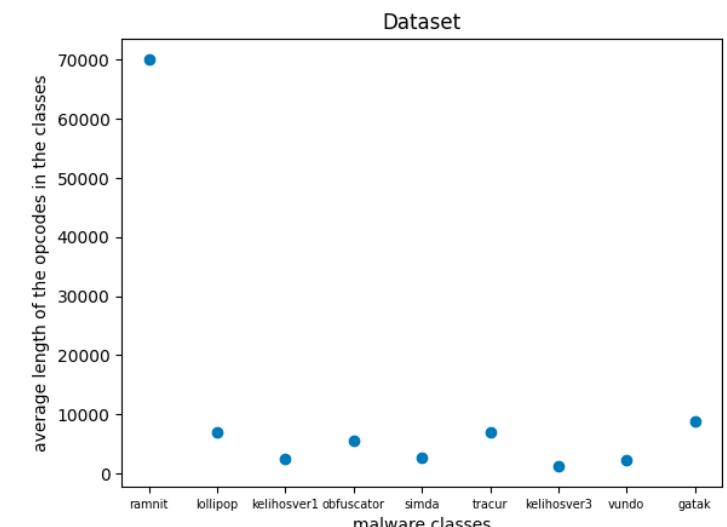
# Models: CNN A



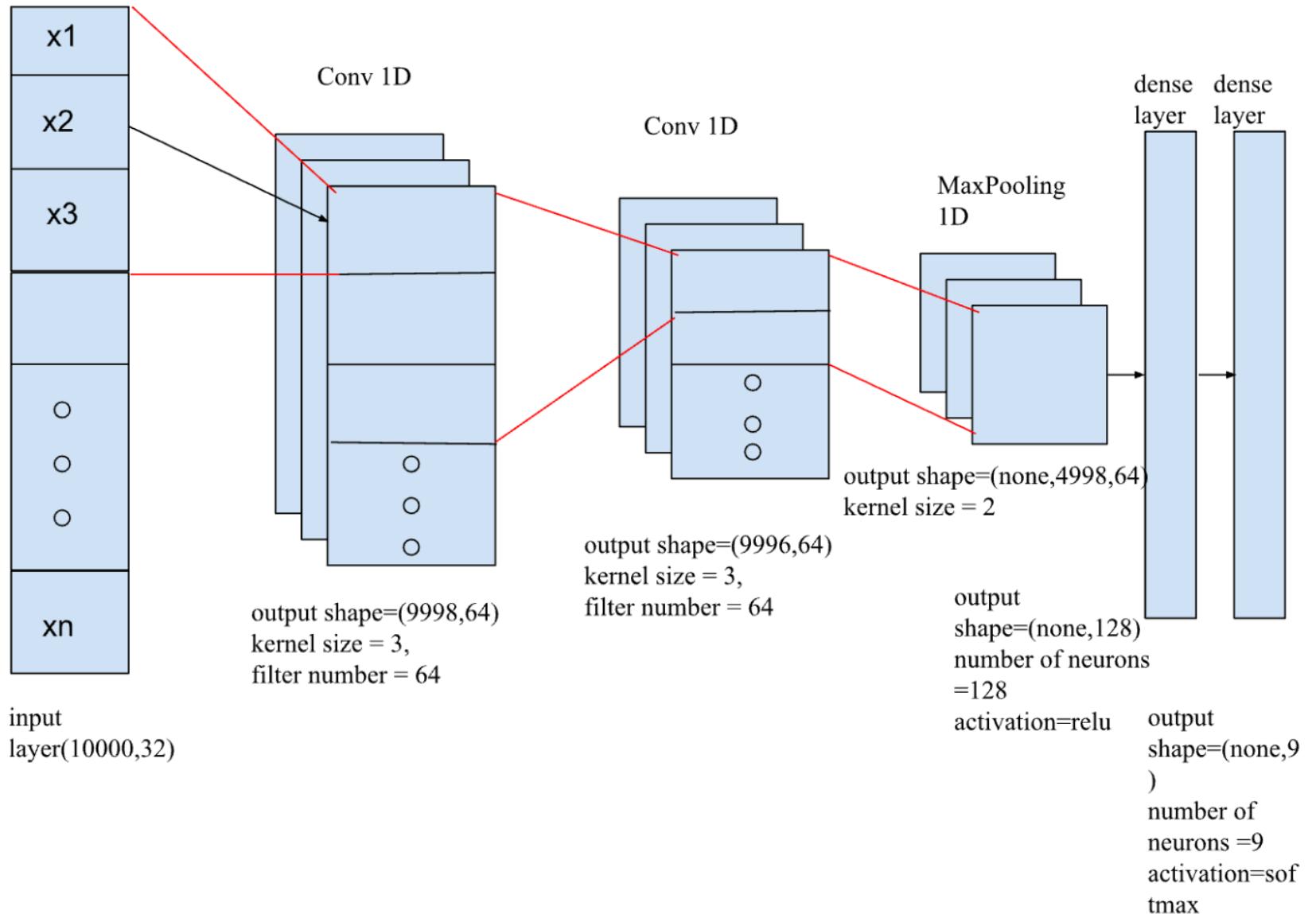
# Models: Natural Language Processing Modality- Word Embedding



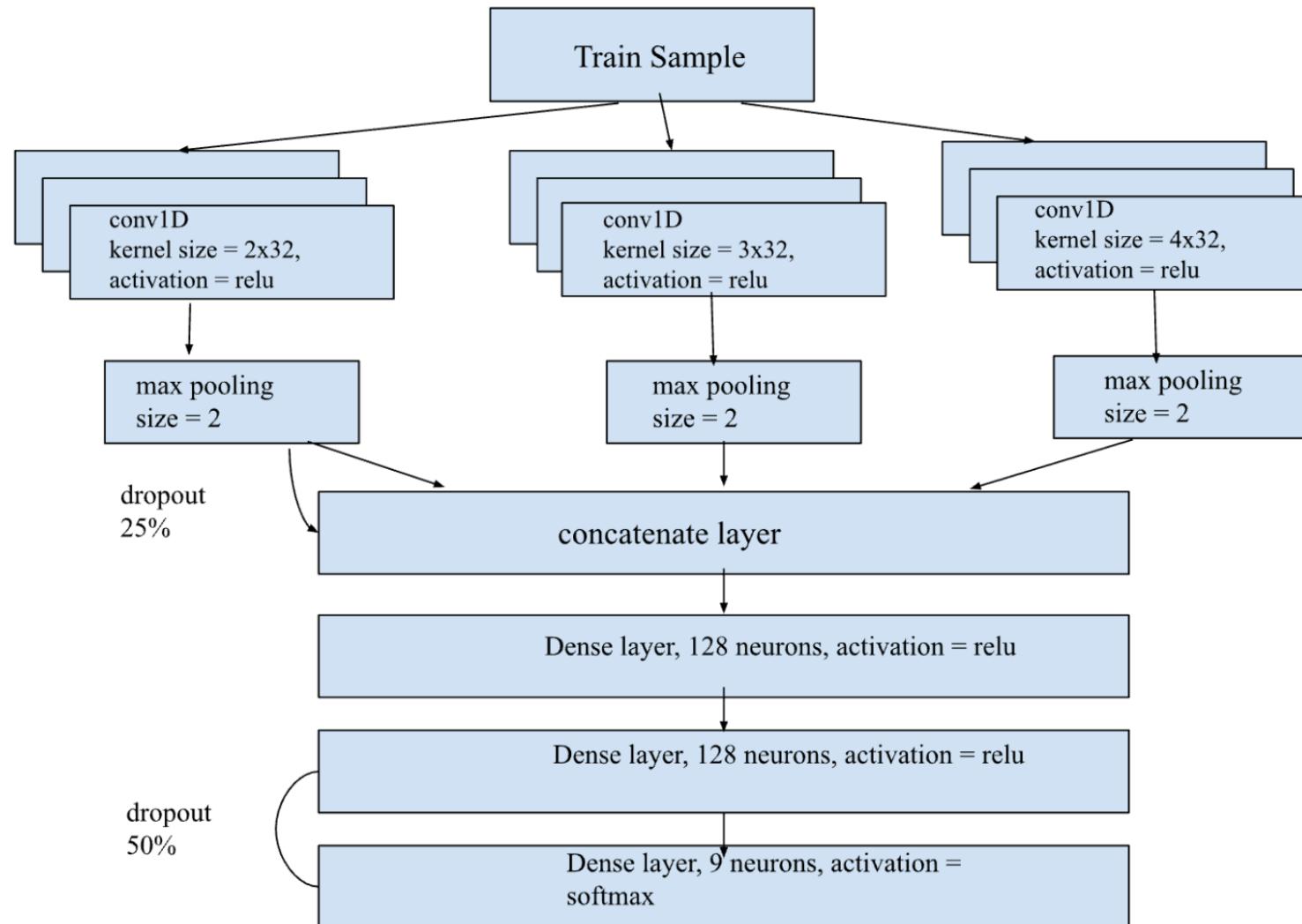
Predictive Language Model: Skip-grams  
Word Embedding Size( $E$ ) = 32  
Window Size = 5  
Vocabulary Size( $V$ ) = 443  
Sequence Length( $N$ ) = 10000



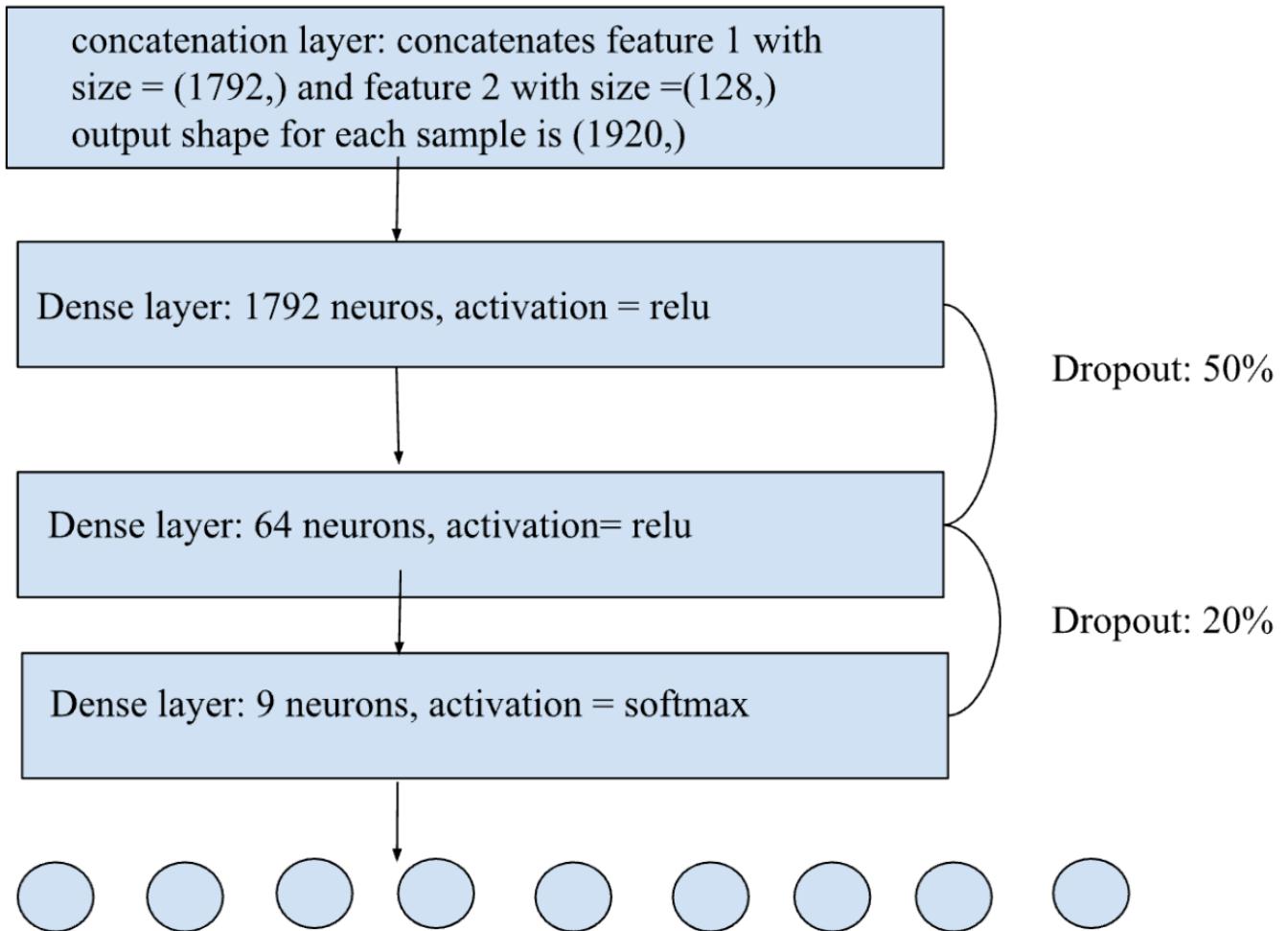
# Models: Natural Language Processing Modality - CNN B



# Models: Natural Language Processing Modality - CNN C



# Models: Bimodal Sequential Model

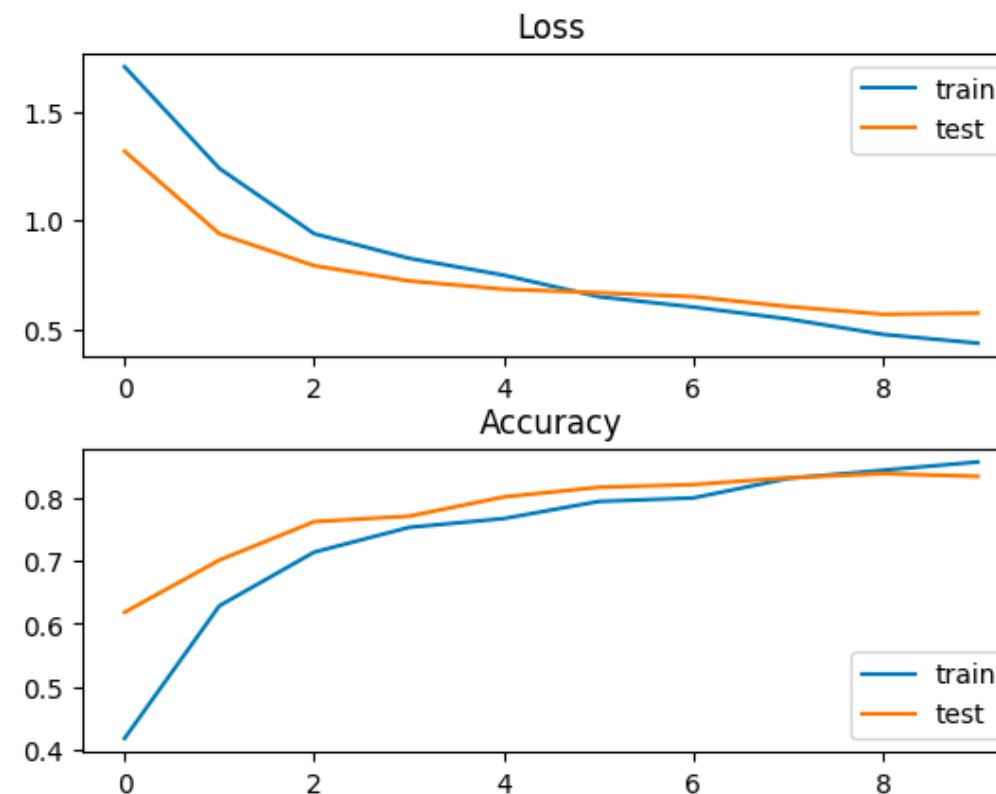
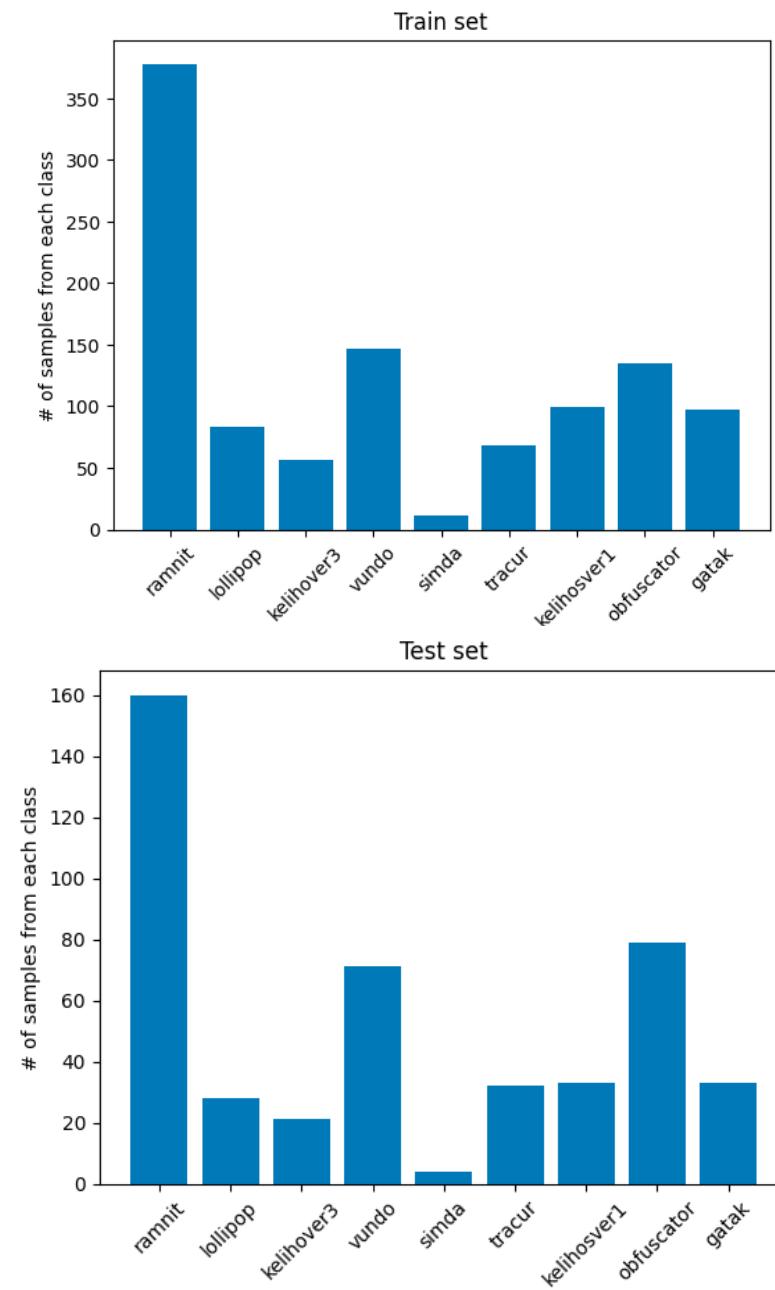


loss = categorical\_crossentropy, optimizer = adam

# Experimental Results &Discussion

- Image Classification Modality
- Natural Language Processing Modality
- Bimodal Sequential Model

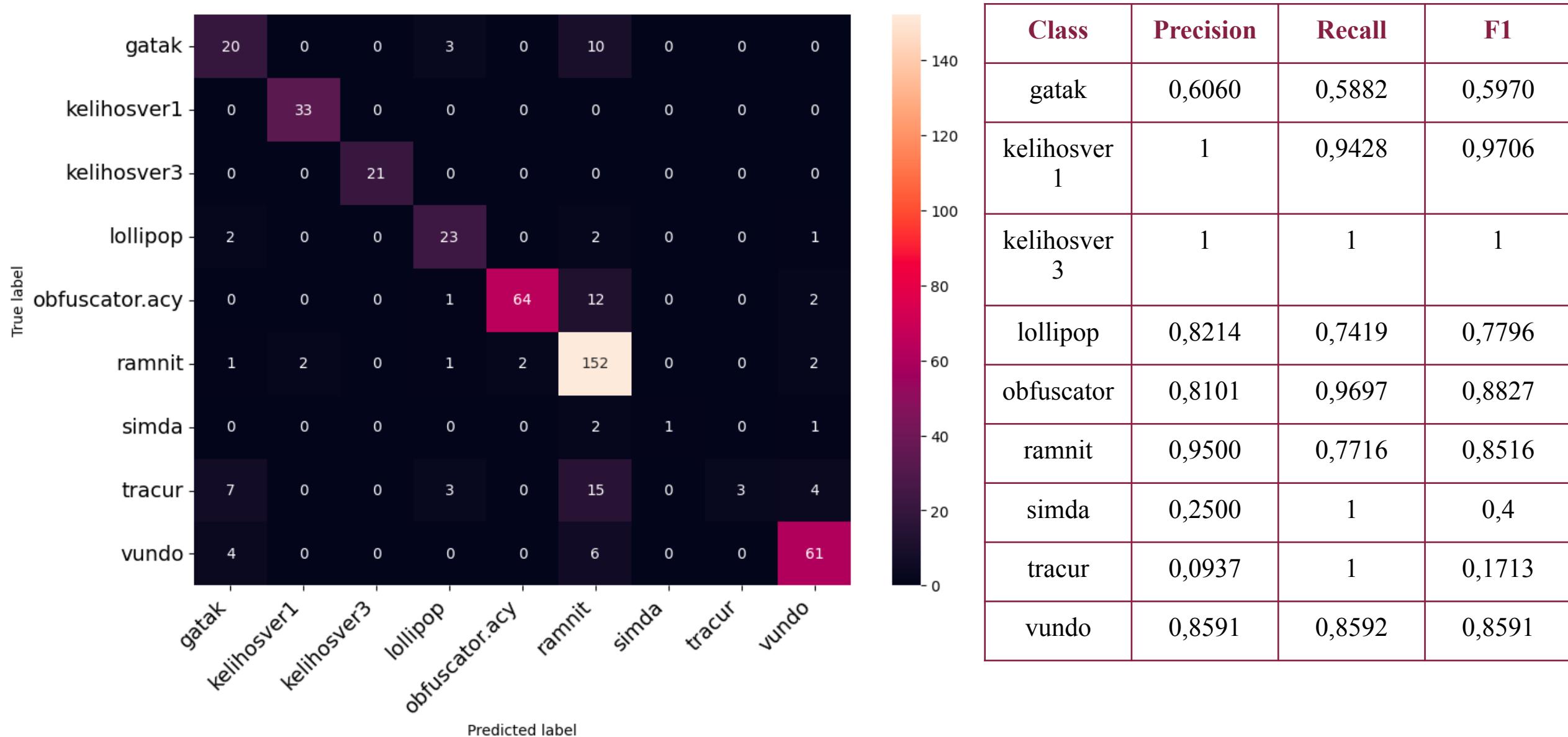
# Results: Image Classification Modality-CNN A



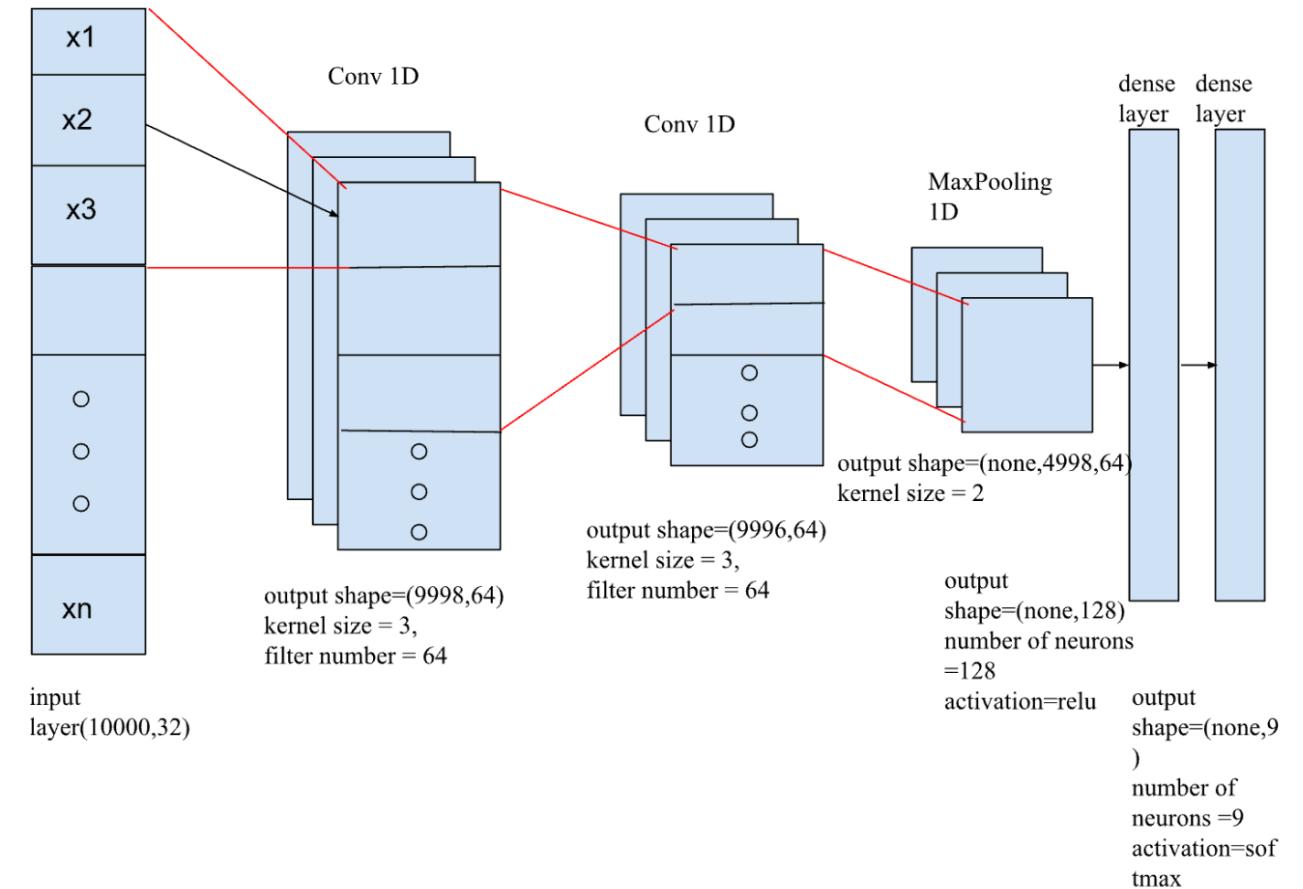
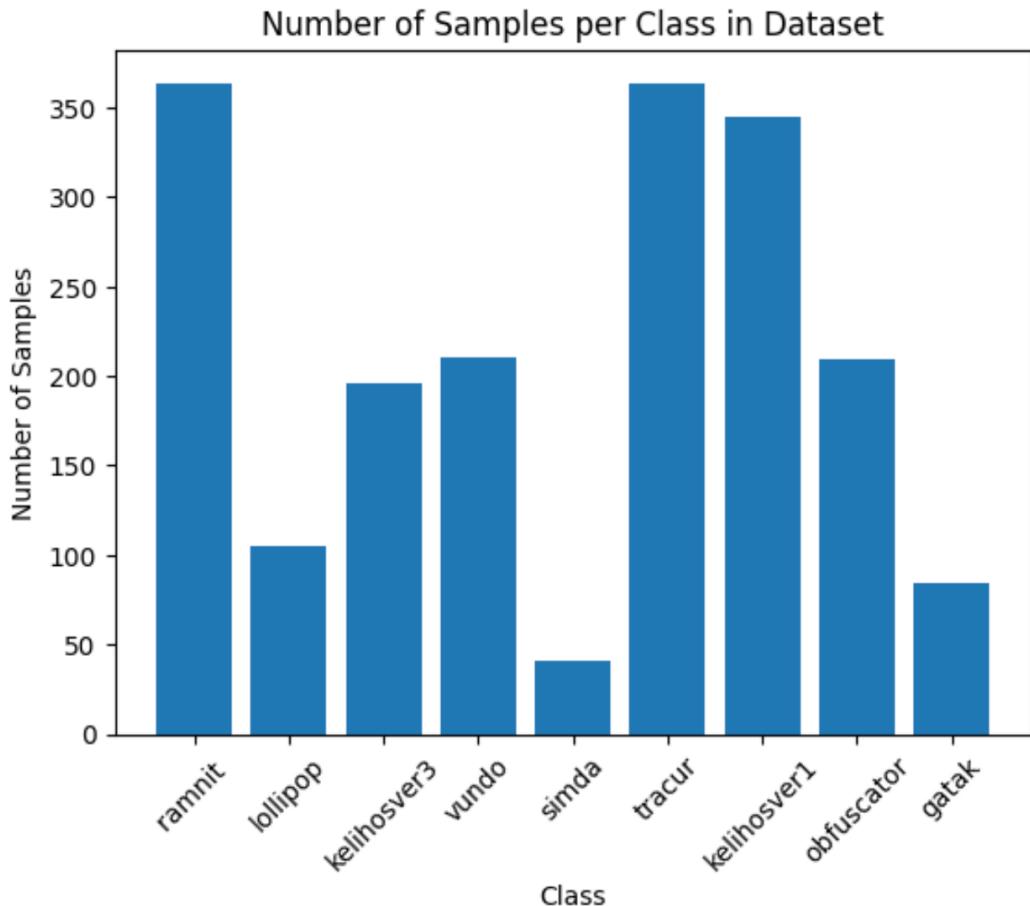
Test Accuracy: 0.8120

Google Collab environment with 25 RAM and 166.77 GB disk capacity. GPU and TPU runtimes are up to 12 hours and the GPUs are K80, P100, T4.

# Results: Image Classification Modality-CNN A - Confusion Matrix

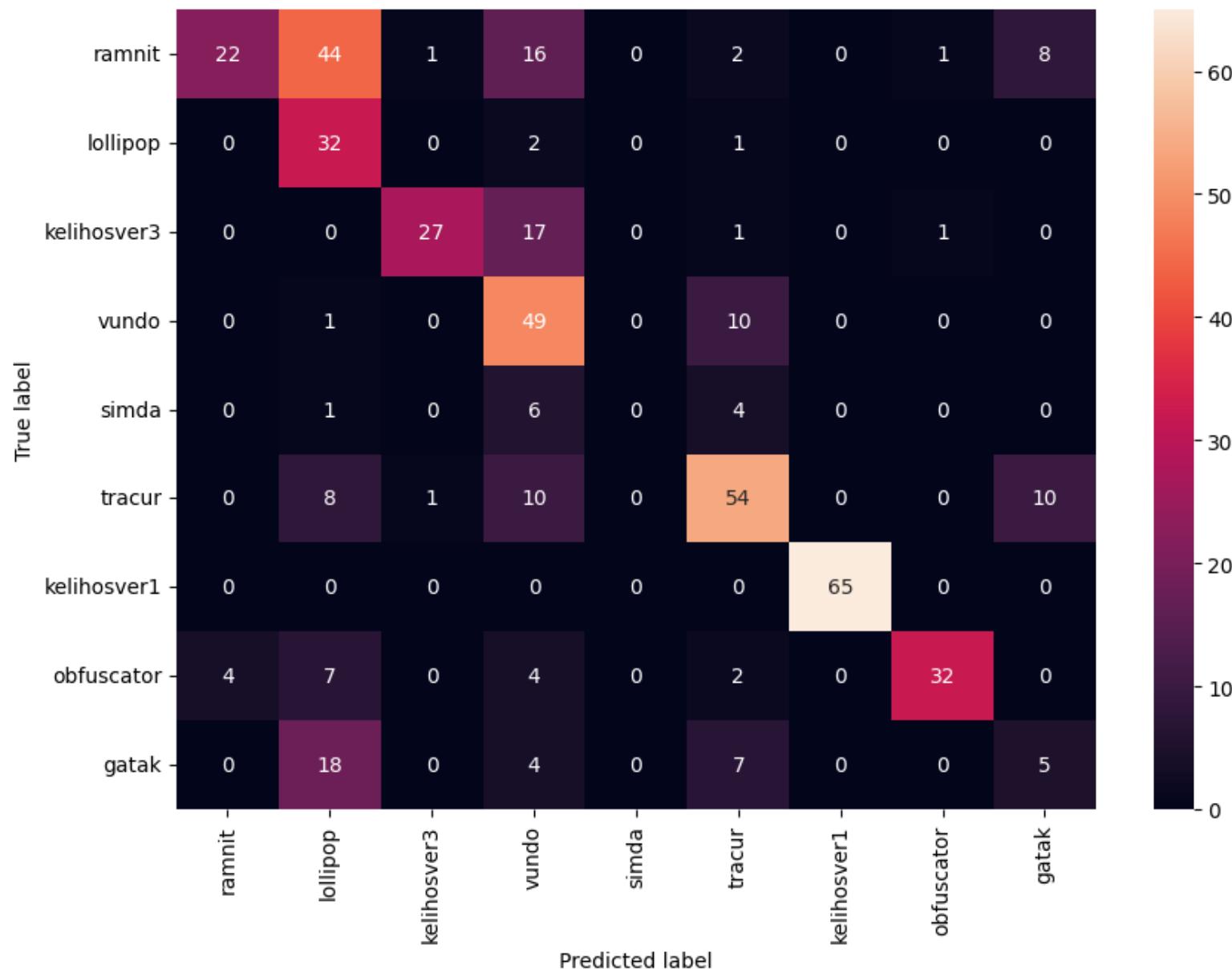


# Results: NLP Modality - CNN B



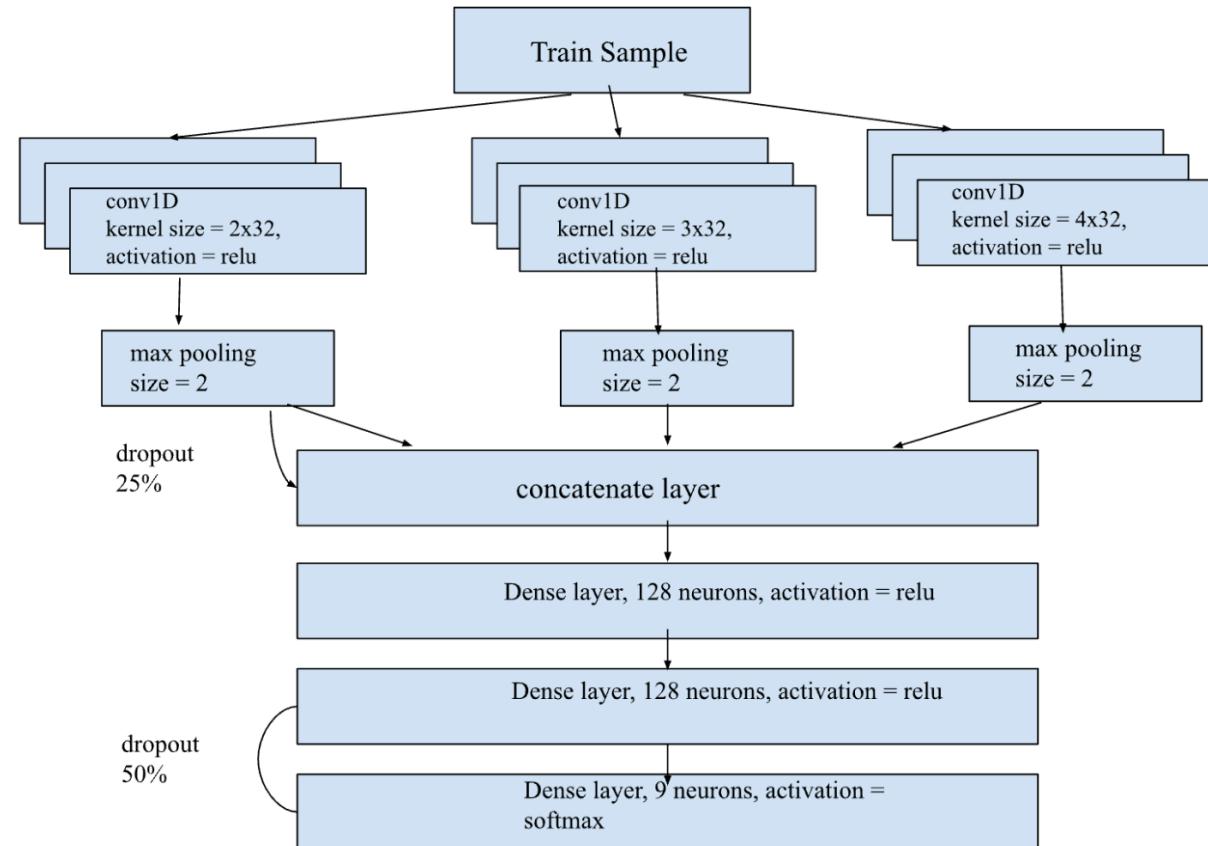
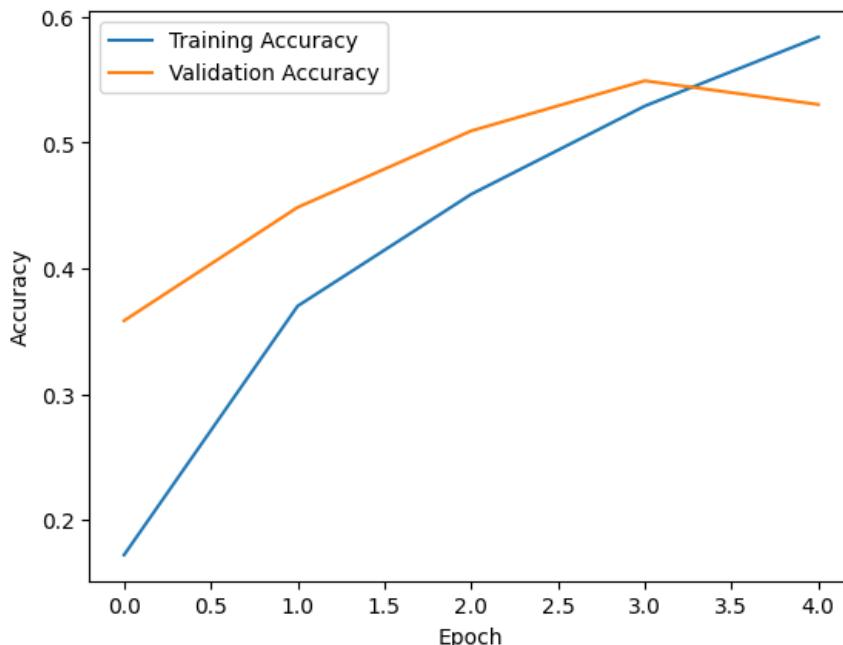
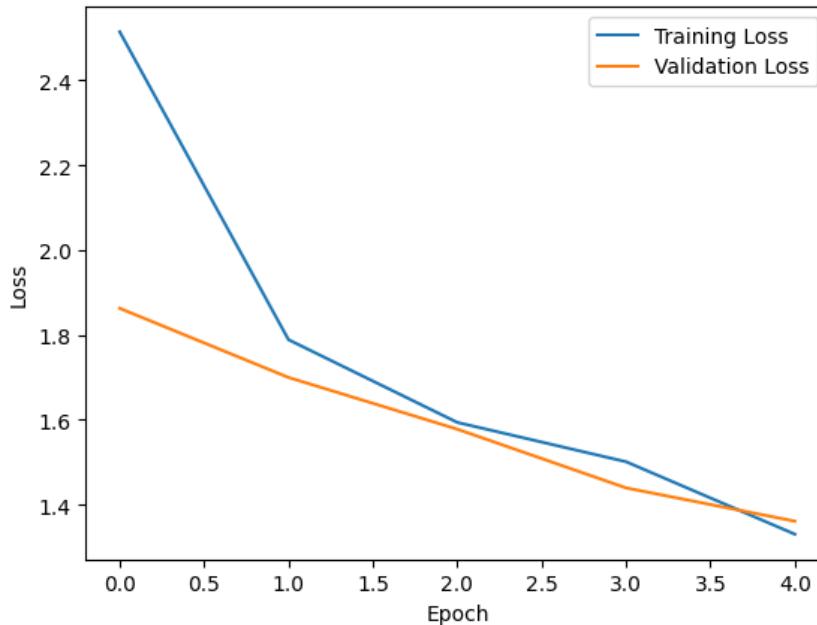
Test Accuracy:  
0.6771

# Results: NLP Modality - CNN B



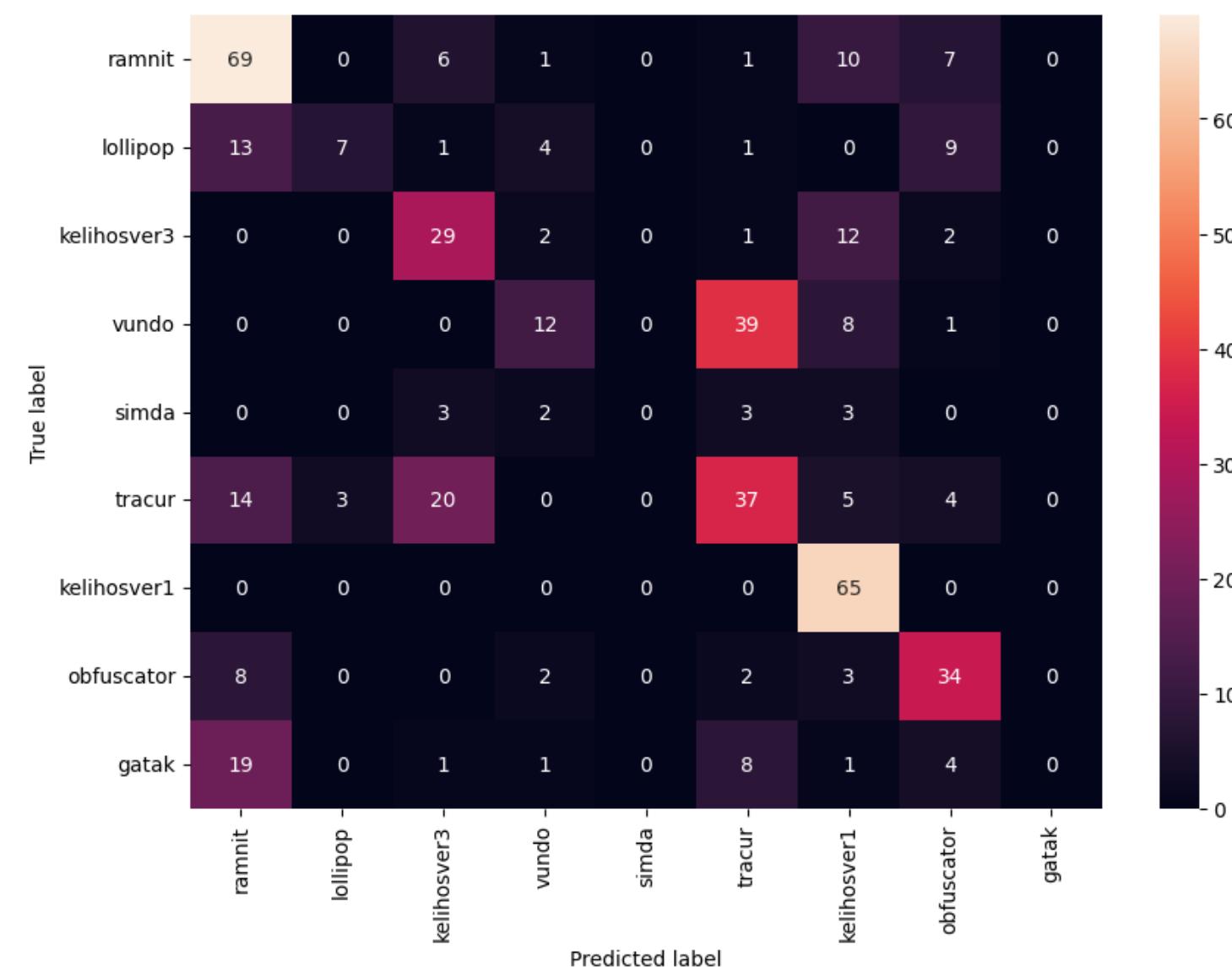
class	precision	recall	F1
ramnit	0,2340	0,8461	0,3666
lollipop	0,9142	0,2883	0,4384
kelihosver 3	0,5869	0,9310	0,7199
vundo	0,8167	0,4537	0,5833
simda	0	undefined	undefined
tracur	0,6506	0,6667	0,6585
kelihosver 1	1	1	1
obfuscator	0,6531	0,9412	0,7711
gatak	0,1470	0,2174	0,1754

# Results: NLP Modality - CNN C



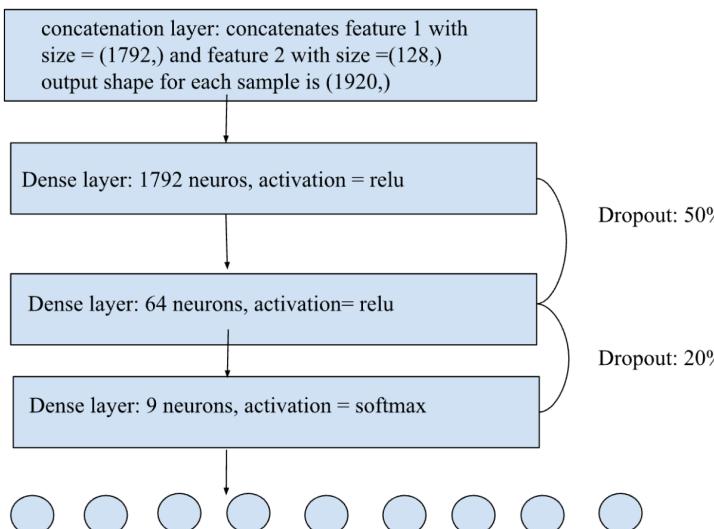
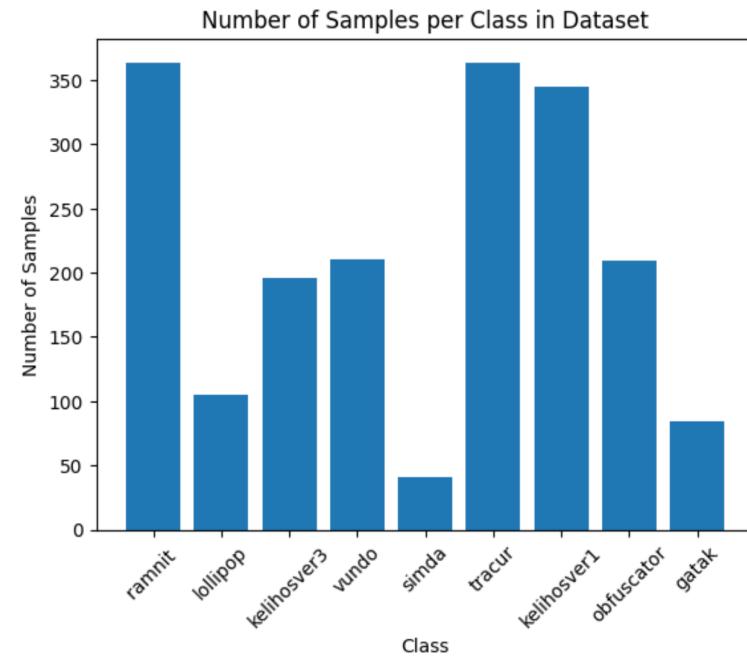
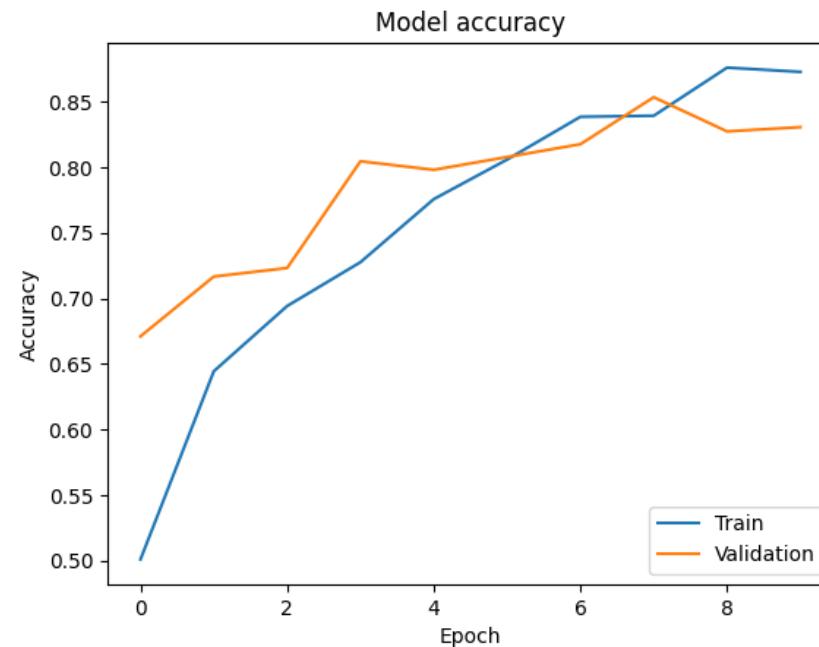
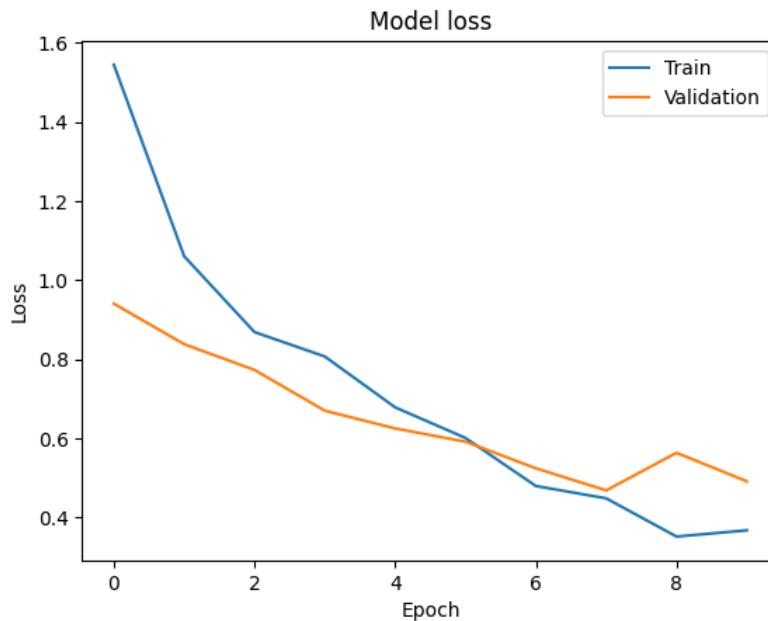
Test Accuracy:  
0.5801

# Results: NLP Modality - CNN C

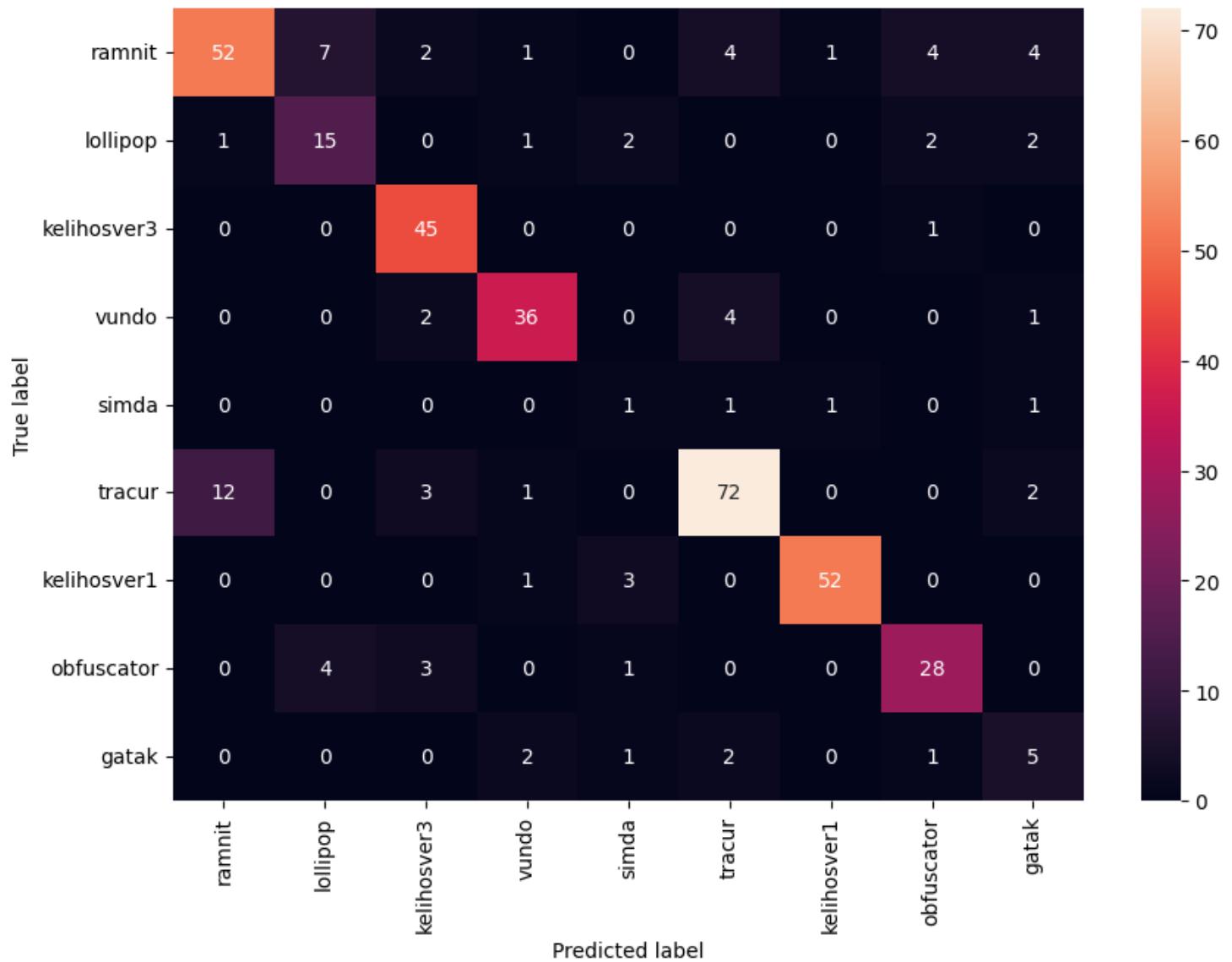


class	precision	recall	F1
ramnit	0,7340	0,5609	0,6359
lollipop	0,2	0,7	0,3111
kelihosver 3	0,6304	0,5088	0,56311
vundo	0,2	0,5	0,2857
simda	0	undefined	undefined
tracur	0,4458	0,4022	0,4229
kelihosver 1	1	0,6075	0,7558
obfuscator	0,6939	0,5574	0,6182
gatak	0	undefined	undefined

# Results: Bimodal Sequential Model



# Results: Bimodal Sequential Model



class	precision	recall	F1
ramnit	0,6933	0,8	0,7428
lollipop	0,6522	0,5769	0,6122
kelihosver3	0,9782	0,8182	0,8911
vundo	0,8372	0,8571	0,8470
simda	0,25	0,125	0,1667
tracur	0,8	0,8675	0,8324
kelihosver1	0,9286	0,9630	0,9455
obfuscator	0,7778	0,7778	0,7778
gatak	0,4545	0,3333	0,3845

# Conclusion

# Conclusion



- Expanding the scope of the project could involve incorporating detection and classification capabilities into the model.
- Dynamic feature extraction or extracting other features from the asm files such as function calls.
- Expand the allowable input opcodes to include the maximum number found in any file within the dataset,
- Grid search to optimize hyperparameters, identifying the best parameters for the model
- Use of class weights
- Replace CNN C with a more effective feature extraction model

# References



- [1]. D. Gibert, "Convolutional Neural Networks for Malware Classification."
- [2]. M. Mimura and R. Ito, "Applying NLP techniques to malware detection in a practical environment - International Journal of Information Security," *SpringerLink*, 06-Jun-2021. [Online]. Available: <https://link.springer.com/article/10.1007/s10207-021-00553-8>.
- [3]. M. Kalash, M. Rochan, N. Mohammed, N. D. B. Bruce, Y. Wang and F. Iqbal, "Malware Classification with Deep Convolutional Neural Networks," 2018 9th IFIP International Conference on New Technologies, Mobility and Security (NTMS), Paris, France, 2018, pp. 1-5, doi: 10.1109/NTMS.2018.8328749.
- [4]. D. Gibert, C. Mateu and J. Planes, "Orthrus: A Bimodal Learning Architecture for Malware Classification," 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, 2020, pp. 1-8, doi: 10.1109/IJCNN48605.2020.9206671.

Thank you very much for listening.

