KutralNet: A Portable Deep Learning Model for Fire Recognition

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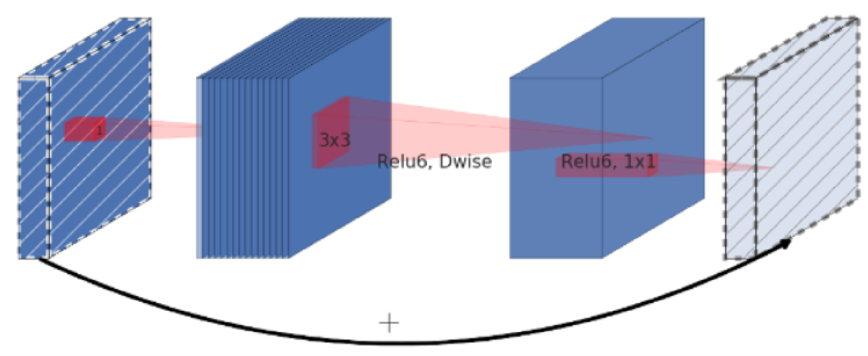
1. Deep Learning (DL) for fire recognition

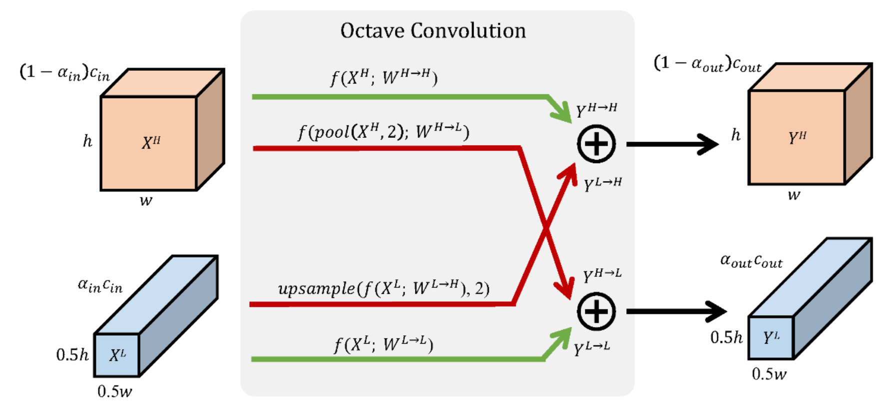
- DL is a promising approach to fire recognition from still images due to its color, texture, and lack of fixed shape [1].
- DL approaches are still challenging for restricted hardware devices by the computational resources and model's complexity.
- DL for mobile devices intends to address these challenges.

2. Fundamental Convolutional Blocks

The inverted residual block[2], the depth-wise[3] and octave[4] convolutions are techniques to reduce the model's size and computation complexity.



The inverted residual block uses the separable depth-wise convolution, followed by a point wise convolution. Adapted from [2].

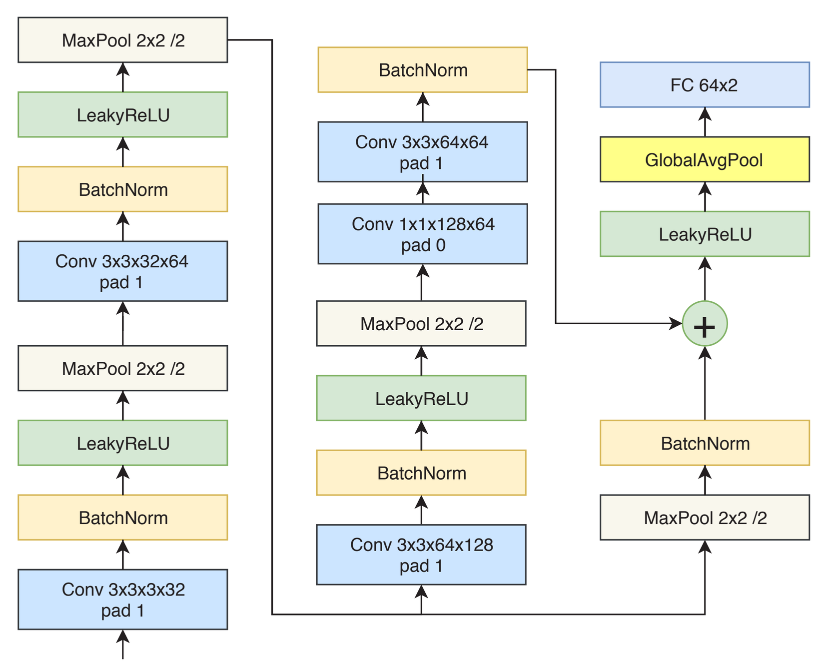


The octave convolution design. The green arrows update information, while red arrows exchange information between the two frequencies. Adapted from [4].

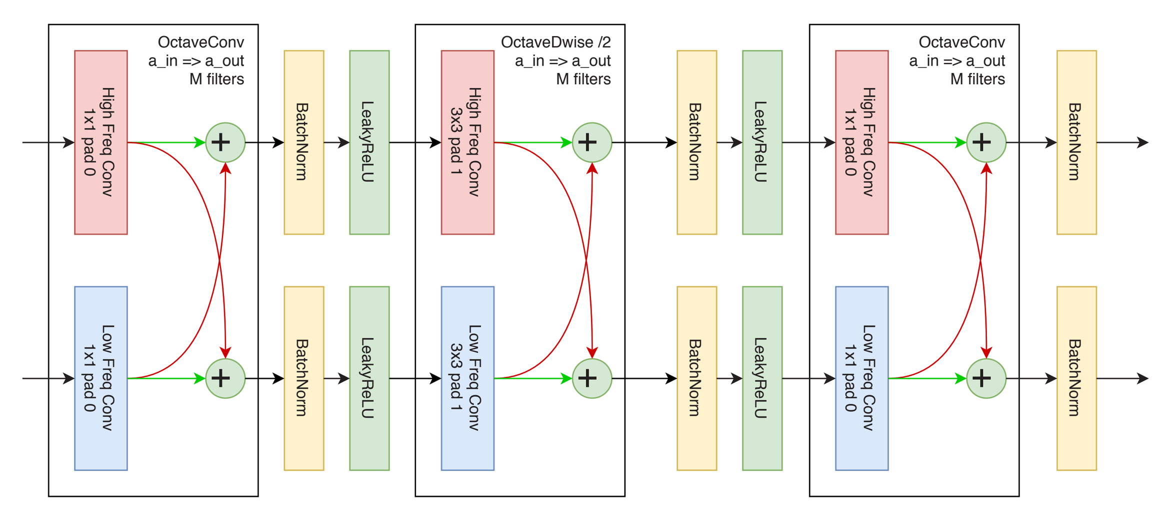
3. KutralNet Architecture

- We propose a low-complexity model to fire recognition inspired by FireNet[5], OctFiResNet[6], and a custom ResNet50[7], called KutralNet*.
- Additionally, we develop three portable models from the fundamental convolutional blocks.

The KutralNet architecture. Comprises three convolution layer blocks with a global average pooling which delivers the features to the fully connected (FC) layer with one neuron for each exit class. Consecutively, a softmax activation function is implemented at the top of the network.



The KutralNet Mobile Octave resultant block. The most to left and right of the block present a point-wise convolution and, in the middle, the depth-wise convolution, all combined with the octave convolution with $\alpha = 0.5$.



The computational cost of each implemented model represented as parameters and flops.

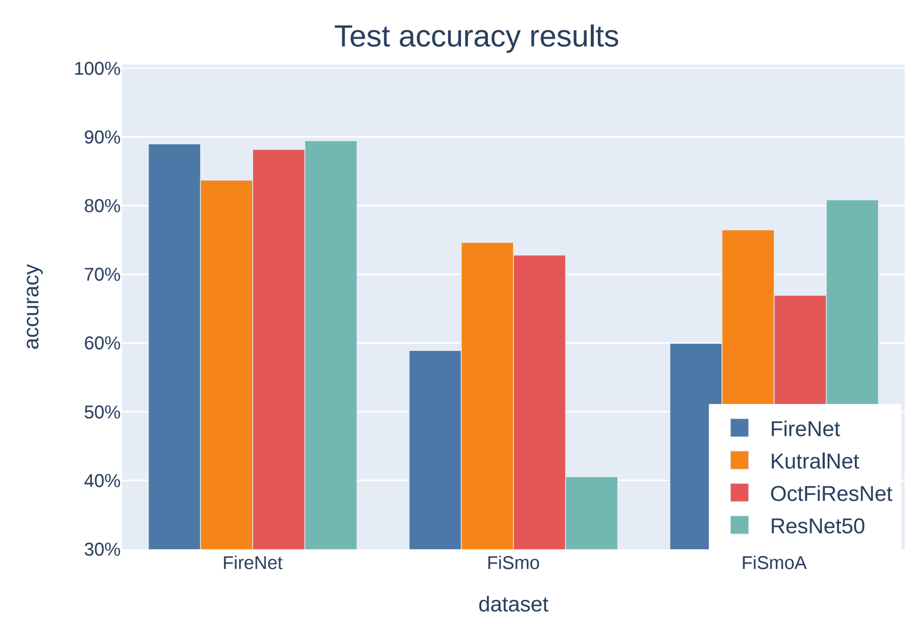
Model$_{(InputSize)}$	Parameters	Flops
ResNet50$_{(224x224)}$	31.91M	4.13G
OctFiResNet$_{(96x96)}$	956.23K	928.95M
FireNet$_{(64x64)}$	646.82K	-
KutralNet$_{(84x84)}$	138.91K	76.85M

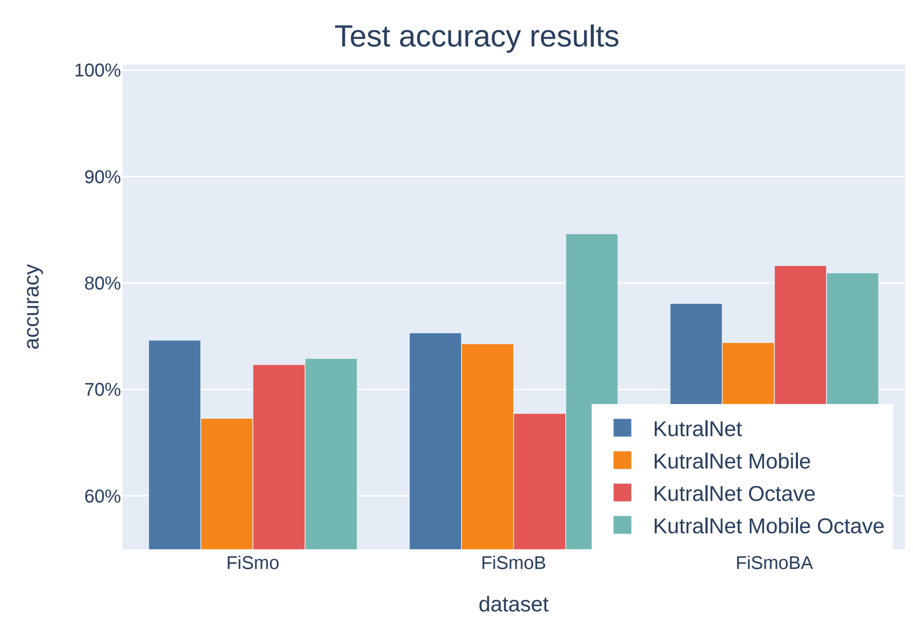
The computational cost of each KutralNet portable variation represented as parameters and flops.

Model$_{(InputSize)}$	Parameters	Flops
KutralNet$_{(84x84)}$	138.91K	76.85M
KutralNet Mobile$_{(84x84)}$	173.09K	43.27M
KutralNet Octave$_{(84x84)}$	125.73K	29.98M
KutralNet Mobile Octave$_{(84x84)}$	185.25K	24.59M

4. Results

The **test accuracy of each model** trained with different datasets and tested with FireNet-Test. The ResNet50 version gets better performance with the FiSmoA, followed by KutralNet.





The **test accuracy of each portable model** trained with different datasets and tested with FireNet-Test. The KutralNet Mobile Octave and KutralNet Octave outperforms the baseline results.

5. Conclusions

- Our **KutralNet model performs better** than previous models for fire recognition as a **lightweight approach.**
- **KutralNet Mobile Octave** achieves a good performance **reducing the baseline model's complexity.**
- As future works are considered to **extend the portable approach to fire recognition and detection** using a bounding box.

6. References

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* We took **inspiration from Mapuche language** or Mapudungun where **kütral means fire**;

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