layer, as there is no need to store neural activities and gradients. On CIFAR-10 input dimensions, our model consumes 0.82M parameters, whereas an identical BP (rep*) architecture requires 1.06M parameters.

Discussion. Our research is a proof of concept that the introduction of the Convolutional Channel-wise Goodness in the Forward-Forward Algorithm enables the algorithm to handle complex problems better through simultaneous feature extraction and separation. Our results demonstrate that CWG outperforms significantly other non-backpropagation approaches in both testing accuracy and convergence rate, especially in comparison with the other CNN-based FF implementations supporting our claim that Channel-wise Goodness enables the FF algorithm to work better with CNNs. This is a significant step forward for the Forward-Forward Algorithm since the gap observed between the original FF algorithm and the well-established backpropagation techniques is narrowed while eliminating the need for the construction of negative data. This was achieved without the utilization of high-level regularization and architecture techniques that appear in state-of-the-art backpropagation implementations and signifies the potential for further improvements in this direction.

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