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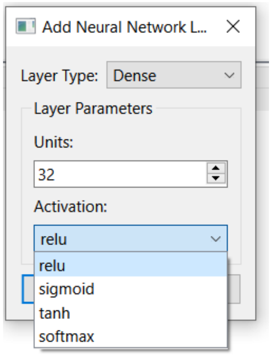
Homework Assignment #3:
Deep Learning Integration

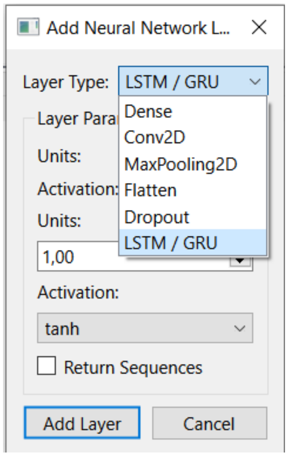
Ertuğrul Bayraktar

Due to: May 25, 2025

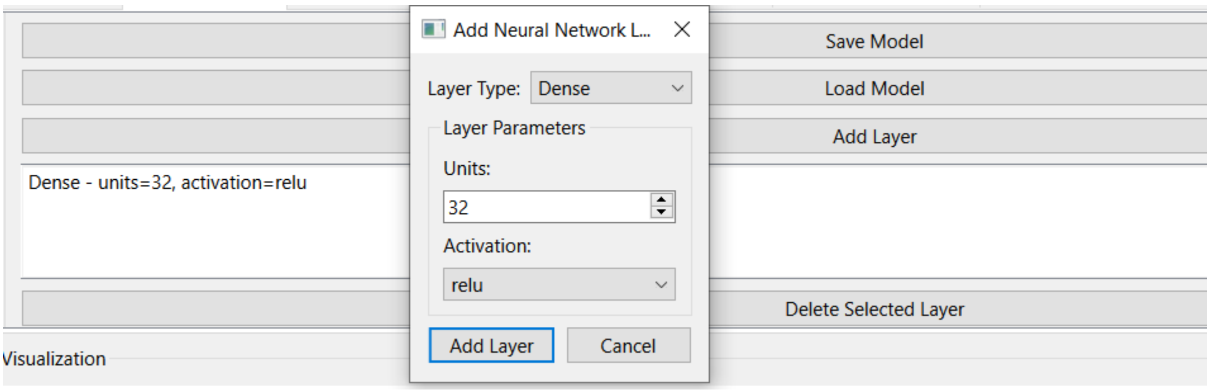
- I added Configurable hidden layers (e.g., 128 → 64 → 32) with activation functions (ReLU, Sigmoid, Tanh) via 'Add Layer' button under update_params()



- I added LSTM/GRU layers for sequence data (e.g., time-series) under add_layer_dialog()



- I made GUI to allow dynamic layer addition/removal with add_layer_dialog() and delete_selected_layer(). I added Save/load buttons for model architectures (e.g., .h5 or .json) with save_model() and load_model().



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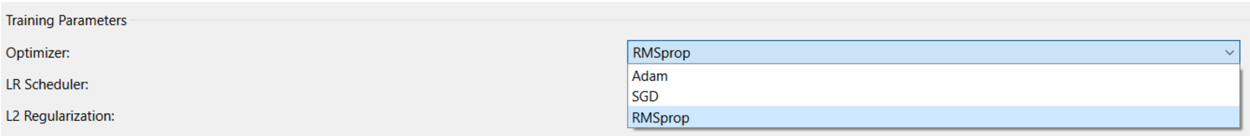
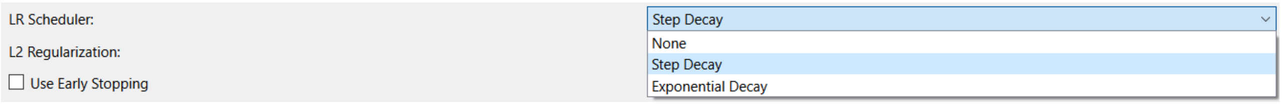
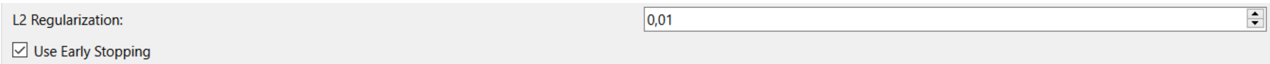
- Adam, SGD and RMSprop optimizers have been implemented under create_training_params_group()



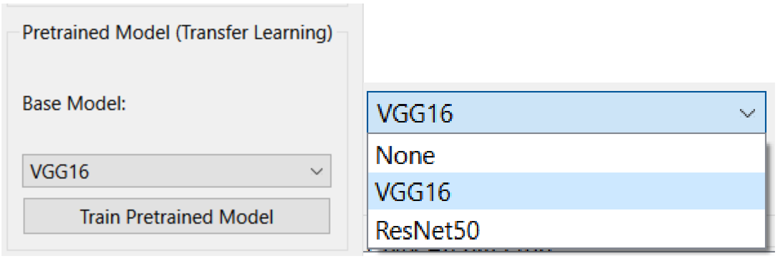
- step decay and exponential decay schedulers have been implemented under create_training_params_group()



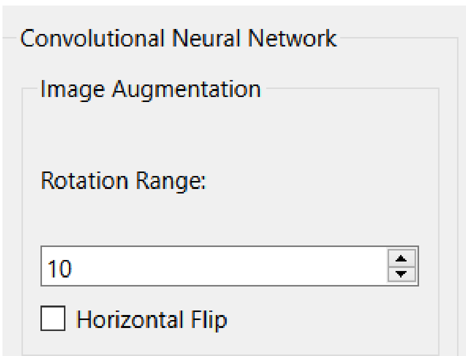
- L2 Regularization and Early Stopping(Dropout) have been implemented under create_training_params_group()



- Pre-trained models (VGG16 and ResNet50) have been implemented via GUI and loaded under train_pretrained_model()



- Rotation Range and Horizontal Flip have been added as options for image augmentation under create_deep_learning_tab()



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Explanation of Architectural Choices

CNN Architectural Choices:
The CNN architecture employs a ***Conv2D*** layer (32 filters, 3×3 kernel) as the first layer to extract spatial features like edges and textures from input images (e.g., MNIST digits). This is followed by a ***MaxPooling2D*** layer (2×2 pool size) to reduce dimensionality and retain dominant patterns while minimizing computational cost. The output is flattened using a ***Flatten*** layer to convert 2D feature maps into a 1D vector, which feeds into a ***Dense*** layer (128 units, ReLU activation) to model non-linear relationships. A final Dense layer with softmax generates class probabilities. This structure prioritizes efficiency for image tasks, balancing feature extraction and computational simplicity.

RNN Architectural Choices:
For sequential data, the RNN architecture uses ***LSTM/GRU*** layers (64 units, tanh activation) to process time-dependent patterns. The LSTM's return_sequences=True parameter preserves temporal outputs for stacked recurrent layers (e.g., multi-step forecasting). A ***Dropout*** layer (0.2 rate) follows to mitigate overfitting by randomly deactivating units during training. The sequence output is flattened via a TimeDistributed(Dense) layer to apply dense operations across time steps, and a final Dense layer with softmax produces predictions. This design emphasizes capturing long-term dependencies while maintaining stability through regularization.

Optimizer Comparison

Adam and SGD with momentum were evaluated to assess their impact on training dynamics. Adam's adaptive learning rate mechanism facilitated rapid convergence, achieving 98.7% training accuracy on MNIST in 10 epochs. Its integration of momentum and RMSProp-like scaling minimized gradient noise, making it ideal for tasks requiring quick results. In contrast, SGD with momentum (0.9) exhibited slower convergence (95.2% accuracy in 15 epochs) but demonstrated greater stability, particularly in later epochs. While Adam excelled in speed, its tendency toward overfitting highlights the need for regularization techniques like dropout or L2 penalties. SGD's fixed learning rate demanded manual tuning but provided predictable updates, making it suitable for scenarios prioritizing model stability over training speed.

- *Unfortunately, I failed in monitoring and visualizing data.*