Proving Adversarial Robustness of Deep Neural Networks

Aiswarya G Raj
CET-IS
IIST INTERN

Guided by:-
Dr. Deepak Mishra
Dr. Mahesh Sreekumar Rajasree

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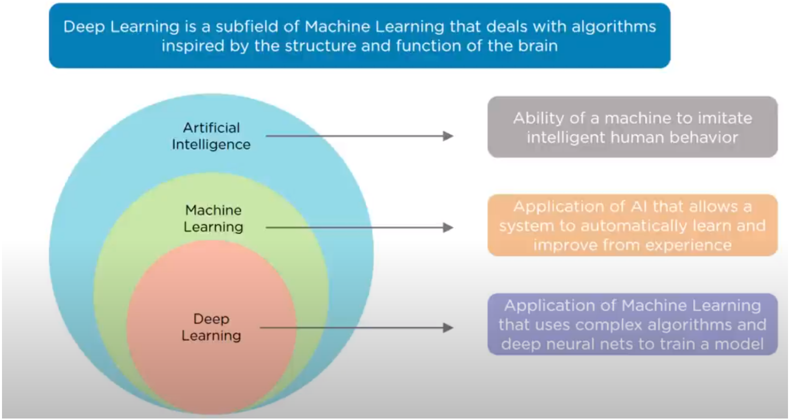
What is Deep Learning?



Deep Learning is a subfield of Machine Learning that deals with algorithms inspired by the structure and function of the brain

Ability of a machine to imitate intelligent human behavior

Application of AI that allows a system to automatically learn and improve from experience

Application of Machine Learning that uses complex algorithms and deep neural nets to train a model

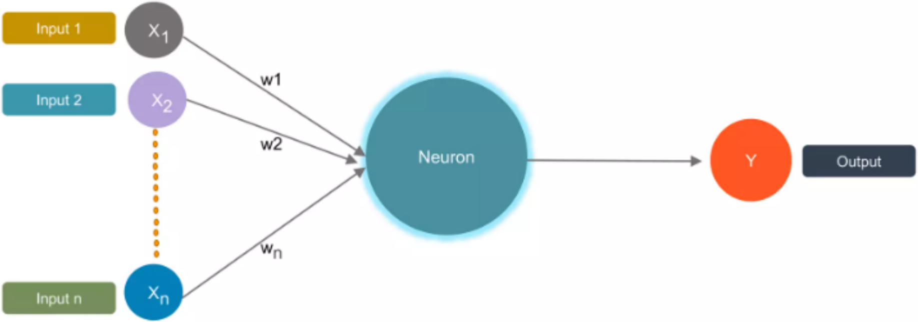
Why do we need Deep Learning?

- Process large amount of data
- Handle complex algorithms
- Achieve best performance with large amount of data
- Feature extraction

Applications of Deep Learning

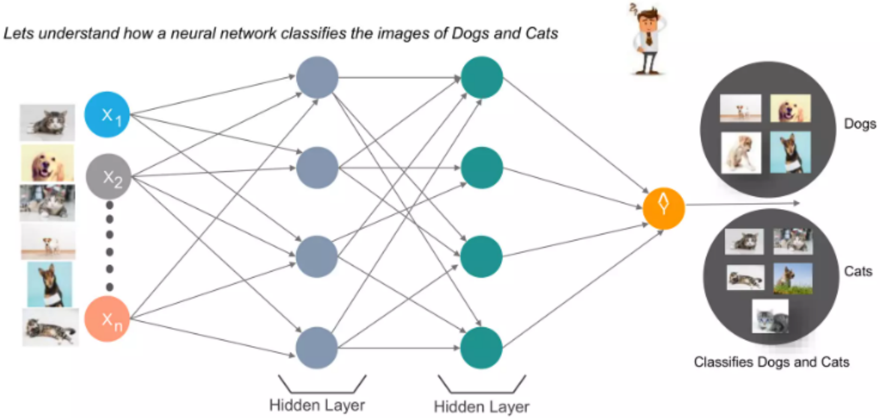
- Detection of Cancer
- Navigation of Robotics
- Machine translation
- Music composition
- Colorization of images
- Autonomous driving cars

What is a Neural Network?



- Deep learning works on neural network.
- Neural network is designed based on human brain.
- Smallest component of neural network is neuron.
- Neuron consists of small central unit which receives the input.
- Each input value is multiplied with a weight and is added with a bias value.
- Output from Step 1 (Transfer function) is taken as the input to the Step 2 (Activation function).
- Step 2 produces the final output which is a binary value.

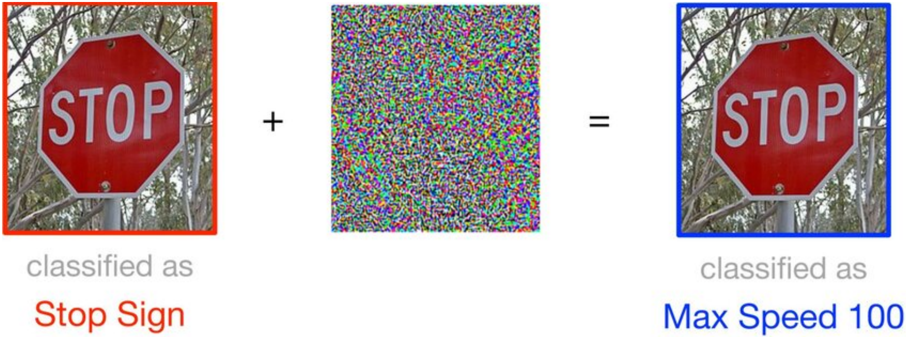
Working of a Neural Network


Lets understand how a neural network classifies the images of Dogs and Cats
X_1
X_2
X_n
Hidden Layer
Hidden Layer
Dogs
Cats
Classifies Dogs and Cats

- Provide labelled training data
- Training:
  - Iterative process
  - Input is given, weights and bias keep changing during each iteration
- Testing:
  - Fresh set of inputs are fed into the network
  - Checking whether accuracy is getting similar or not
  - Accuracy become maximum when the values for weight and bias become optimal

Adversarial Robustness

- Adversarial robustness refers to the ability of a machine learning model to maintain its performance and accuracy when exposed to adversarial examples.
- Adversarial examples are data points which are indistinguishable from our dataset but lead to wrong predictions.
- Adversarial inputs refers to inputs specifically designed to deceive a Deep Neural Network.
- These inputs are generated by making small changes to correctly classified inputs, causing the DNN to misclassify them.
- For example, an image of a stop sign.


classified as
Stop Sign
+
=
classified as
Max Speed 100

Reluplex

- Reluplex is an extension of the Simplex algorithm specifically designed to handle the piecewise linear nature of ReLU functions.
- It enables effective verification of ReLU-based neural networks.
- For each ReLU node, it introduces two linear constraints: $y \geq 0$, $y \geq x$.
- The algorithm determines whether the ReLU node is active (y=x) or inactive (y=0).
- It enhances the safety and reliability of AI systems.
- It can verify local robustness for networks with hundreds of nodes, but global robustness is limited to smaller networks with a few dozen nodes due to the increased complexity.

Comprehended Paper

“Towards proving the adversarial robustness of deep neural networks”

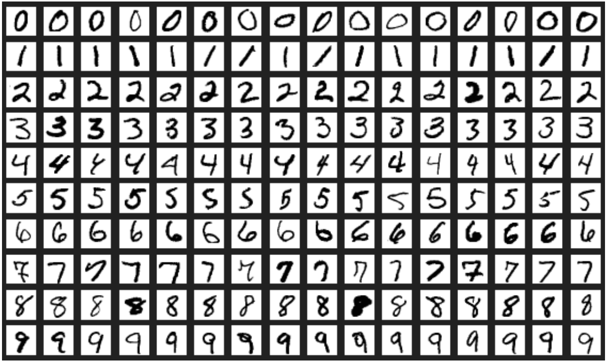
- It explores how neural networks can resist adversarial attacks by studying existing research on adversarial robustness and input perturbations designed to deceive the network.
- This paper focuses on understanding and proving the robustness properties of neural networks, ensuring they maintain performance and accuracy even when faced with adversarial inputs.
- The study investigates different types of robustness in neural networks, including resistance to adversarial attacks and overall stability across various conditions.

- The paper addresses practical aspects of verifying robustness in real-world networks, focusing on scalability and computational feasibility of the techniques.
- The authors present initial findings on establishing robustness properties specifically for ACAS Xu networks used in unmanned aircraft collision avoidance systems.
- The paper identifies unresolved research issues and outlines future plans involving new techniques, methodologies, or experiments to address these challenges.

Implementation and Output

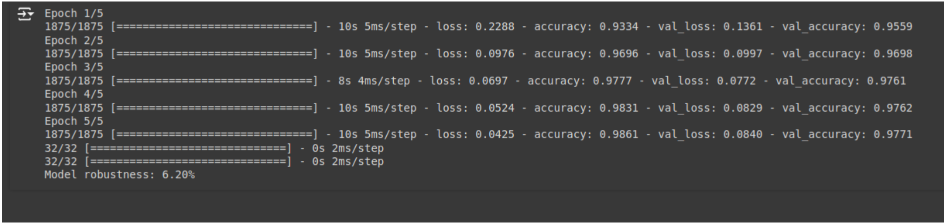
- The main objective of the code is the process of creating a neural network, generating adversarial examples to test the network and verifying the network's robustness against these adversarial examples.
- MNIST dataset is used to define, compile, and train a neural network model for a classification task.
- The dataset is relatively small and easy to handle, making it suitable for quick experiments and prototyping.
- The dataset is easily accessible through various machine learning libraries such as TensorFlow and Keras.

- Here's an example of how the images and labels look in the MNIST dataset:



- The Fast Gradient Sign Method (FGSM) is an algorithm used to generate adversarial examples.
- It is commonly used to evaluate the robustness of machine learning models, especially neural networks, against adversarial attacks.
- Robustness is evaluated by comparing the model's predictions on original inputs versus adversarially perturbed inputs.

Output



```
Epoch 1/5
1875/1875 [==============================] - 10s 5ms/step - loss: 0.2288 - accuracy: 0.9334 - val_loss: 0.1361 - val_accuracy: 0.9559
Epoch 2/5
1875/1875 [==============================] - 10s 5ms/step - loss: 0.0976 - accuracy: 0.9696 - val_loss: 0.0997 - val_accuracy: 0.9698
Epoch 3/5
1875/1875 [==============================] - 8s 4ms/step - loss: 0.0697 - accuracy: 0.9777 - val_loss: 0.0772 - val_accuracy: 0.9761
Epoch 4/5
1875/1875 [==============================] - 10s 5ms/step - loss: 0.0524 - accuracy: 0.9831 - val_loss: 0.0829 - val_accuracy: 0.9762
Epoch 5/5
1875/1875 [==============================] - 10s 5ms/step - loss: 0.0425 - accuracy: 0.9861 - val_loss: 0.0840 - val_accuracy: 0.9771
32/32 [==============================] - 0s 2ms/step
32/32 [==============================] - 0s 2ms/step
Model robustness: 6.20%
```

- The model trains for 5 epochs, improving in both training and validation accuracy while reducing loss.
- The final accuracy on the validation set is high, at around 97.71%.
- The model's robustness is relatively low at 6.20%, suggesting that it might still be susceptible to adversarial examples or perturbations.

Conclusion

- Deep Learning solves complex problems, achieves high accuracy in tasks like image and speech recognition.
- Neural Networks are computational models inspired by the human brain, consisting of interconnected layers of nodes.
- Adversarial Robustness is the ability of a neural network to resist adversarial attacks.
- Reluplex is a tool for verifying properties of neural networks, specifically those using ReLU activation functions.
- Successfully trained model with high validation accuracy (97.71%) and noted a robustness score of 6.20%, indicating areas for improvement in adversarial defense.

Future Enhancement

- Develop and integrate advanced defense mechanisms to enhance model robustness against adversarial attacks.
- Enhance the scalability of verification tools like Reluplex to handle larger neural networks efficiently.
- Train and test the model on more diverse and complex datasets to ensure robustness across various data distributions.
- Implement real-time detection systems to identify and mitigate adversarial attacks during model deployment.
- Explore the application of adversarial robustness techniques in other domains, such as finance, healthcare, and cybersecurity.

Internship Summary

- Gained in-depth knowledge about deep learning, neural networks, and their applications in various fields.
- Studied adversarial robustness and tools like Reluplex to verify the robustness of neural networks.
- Implemented a neural network using the MNIST dataset and generated adversarial examples to test robustness.
- Achieved high validation accuracy (97.71%) but identified low robustness (6.20%), indicating the need for further enhancements.
- Identified potential future enhancements, including better defense mechanisms, scalability improvements, and application across diverse datasets.

Thank you!