Dear Sir,

Here the DNN Identification is used to find the fault in Tie Plate. For the Tie Plate Rating algorithm images of acceptable tie plates and images of faulty tie plates (twisted, shifted or hanging) were used for training and a matching set for testing. While it would have been ideal to utilize similar numbers of acceptable and faulty tie plates for training and testing purposes, this was not practical given the normal rate of occurrence of faulty tie plates for properly maintained track. So we are using the CANDETECTION dataset for finding the minute variation in the faulty places of Tie plate very accurately.

In this approach to overcome the limitations using Deep Learning algorithms, specifically a Deep Neural Network (DNN), to automatically inspect 3D Laser Triangulation images. 3D laser triangulation captures a both a high-resolution image (2D) and a 3D point cloud of the entire track area and can be used at revenue speeds, day or night. DNN is a type of machine learning wherein the computer develops a solution to a complex problem in a way that is like how humans learn (using a neural network). Deep Learning is well-suited to image analysis and has even been demonstrated to improve the accuracy of cancer detection by oncologists when used to analyze images of lymph nodes.

The algorithm development process involved the use of a dataset of 400 images containing both cancerous and non-cancerous cells (identified by a pathologist). Of the 400 images 270 were used for algorithm training purposes and the remaining 130 were used to test the resulting algorithms. During the training process slide images were combined with ground truth data in order to create both positive and negative, 256 x 256 pixel, sample images which were used to teach the DL algorithm how to distinguish between cancerous and non-cancerous cells. Following the training process the DL algorithm was tested against the 130 test images in order to determine algorithm performance.

The CANDETECTION dataset plays a critical role in modernizing and enhancing the efficiency of railroad inspections. By offering a comprehensive collection of annotated data, it enables advanced machine learning and AI-driven systems to identify and address issues in railway infrastructure more effectively.

The image classification algorithm is a seven layer (6 hidden layers and 1 output layer) Supervised Machine Learning (SML) algorithm based on DeepCNet which combines 62,040 weights and 76 biases for a total of 62,116 learnable parameters.

The six hidden layers include: a 5x5 convolution layer with 5 maps, a 3x3 semi-stochastic pooling layer, a 1x1 inception layer, a 5x5 convolution with 10 maps, and a 2x2 semi-stochastic pooling layer that outputs to a fully connected output layer using softmax.

In order to determine if an image contains a fastener, some ballast, a concrete tie or a wooden tie, the DNN first divides each 4,000 pixel x 2,000 pixel image into two 35 x 35 pixel sub-images. Each 35 x 35 pixel image is then labeled by the algorithm as either “fastener,” “ballast,” “wood,” or “concrete” thus creating a “raw labeled” image. Finally, the DNN groups sub images together to form regions which correspond to identified railway components. This is used to eliminate small errors in sub image identification.

* **High-Quality Data**: The CANDETECTION dataset likely includes annotated images or sensor readings of railroad components, such as tracks, ties, and switches, with precise labels for common defects (e.g., cracks, wear, misalignments).
* **AI Training**: It is used to train machine learning algorithms to detect defects automatically with high accuracy, even in complex or variable conditions.
* The dataset supports the development of automated inspection systems that can scan railway tracks in real-time using drones, cameras, or onboard sensors.
* These systems minimize human error, reduce labor-intensive tasks, and increase inspection coverage and frequency.