ITMO UNIVERSITY

DEEP LEARNING METHODS FOR THE PLANT DISEASES DETECTION PLATFORM

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THE REPORTED STUDY WAS FUNDED BY RFBR ACCORDING TO THE RESEARCH PROJECT № 18-07-00829

PLANT DISEASE DETECTION PROBLEM

ECONOMY RISKS

ACCORDING TO THE ALL-RUSSIAN INSTITUTE FOR PLANT PROTECTION, ANNUALLY FROM DISEASES OF PESTS AND WEEDS, GRAIN LOSSES IN RUSSIA REACH 15-29 MILLION TONS, IN 2019 PRICES, LOSSES ARE EQUAL TO **120-212 BILLION. RUBLES**

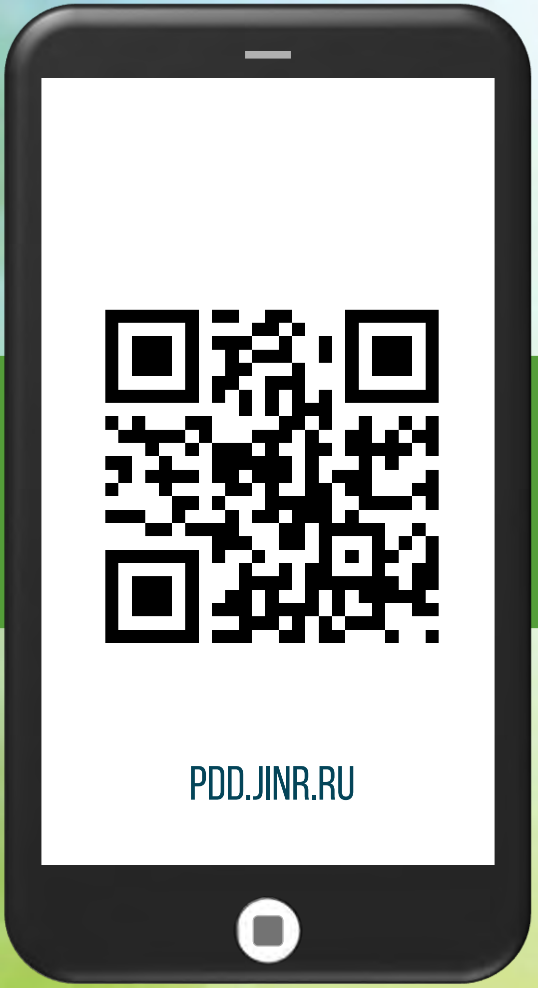
A PROBLEM FOR VILLAGERS

SOMETIMES IT CAN BE DIFFICULT FOR A GARDENER TO IDENTIFY A PLANT DISEASE AND FIND THE NECESSARY INFORMATION ABOUT ITS TREATMENT.

EARLY IDENTIFICATION

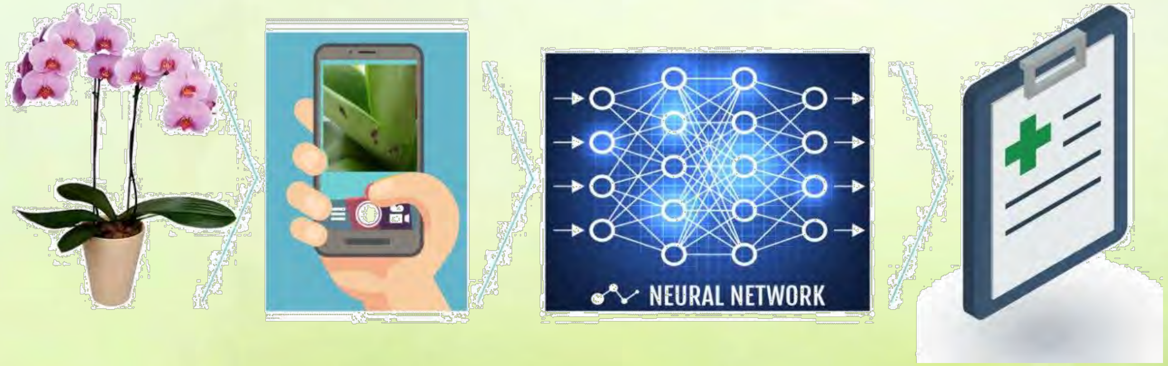
THE ABILITY TO IDENTIFY AFFECTED SHOOTS AND DETERMINE THE TYPE OF DISEASE AT AN EARLY STAGE WILL HELP TO TAKE TIMELY MEASURES AND PREVENT THE SPREAD OF INFECTION.

MAIN GOAL



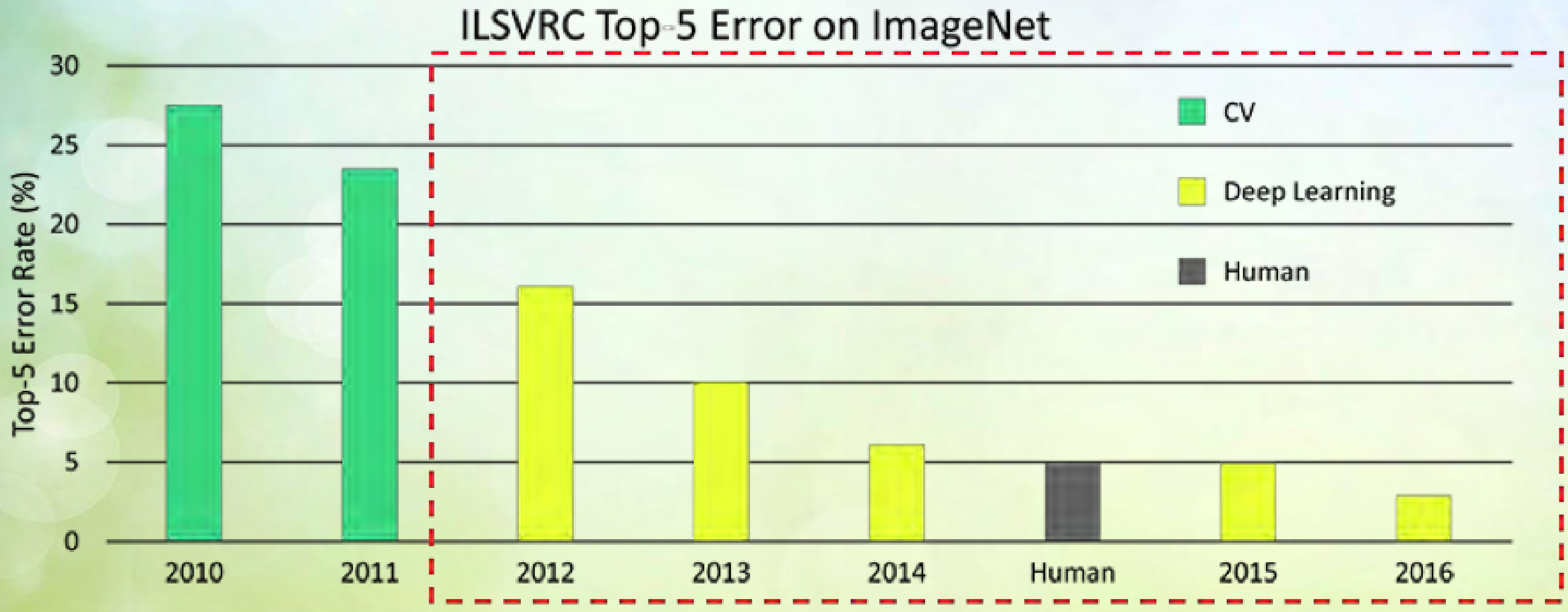
THE MAIN GOAL OF THE RESEARCH IS TO CREATE A MULTIFUNCTIONAL PLATFORM PDDP — PLANT DISEASE DETECTION PLATFORM.

LIT JINR HAS DEVELOPED A PDDP APPLICATION, WHICH ENABLES USERS TO SEND PHOTOGRAPHS AND TEXT DESCRIPTIONS OF DISEASED PLANTS THROUGH THE PDD.JINR.RU WEB PORTAL OR A MOBILE APPLICATION AND FIND OUT THE CAUSE OF THE DISEASE.



THE REVOLUTION IN VISUAL PERCEPTION

IMAGENET Large Scale Visual Recognition Challenge (ILSVRC)



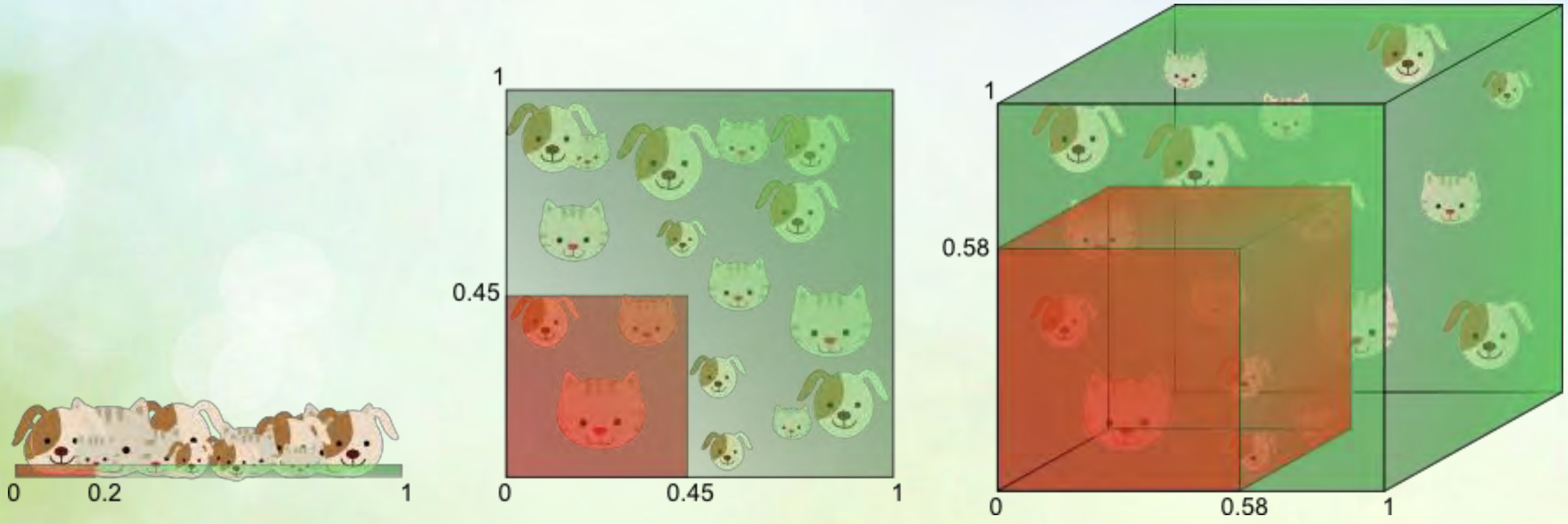
The introduction of Deep Learning techniques drove performance on image categorization from 30% error rates in 2010, down to <2% in 2017 http://pdd.jinr.ru/crops.php

IMAGE DATASET

- 934 IMAGES
- 20 VARIOUS DISEASES
- 5 CROPS:
  - GRAPE
  - WHEAT
  - CORN
  - COTTON
  - CUCUMBERS

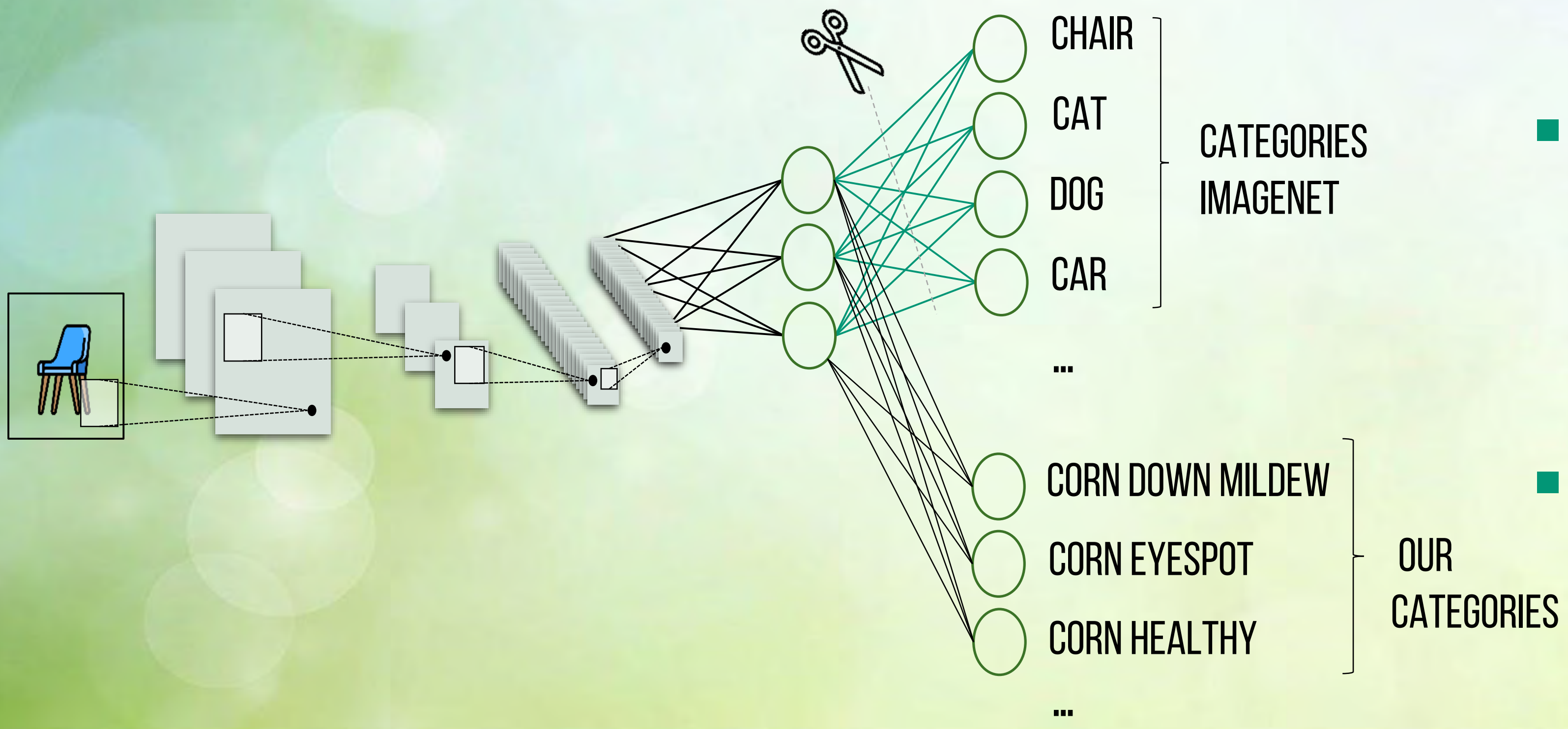
CURSE OF DIMENSIONALITY

THE LARGER THE DIMENSION, THE MORE EXAMPLES ARE NEEDED TO DESCRIBE ALL CASES!



DEEP LEARNING REQUIRES A LARGE TRAINING SAMPLE. PDPP DATASET IS SMALL, SO WE CONSIDERED METHODS THAT ALLOW US TO SOLVE THIS PROBLEM.

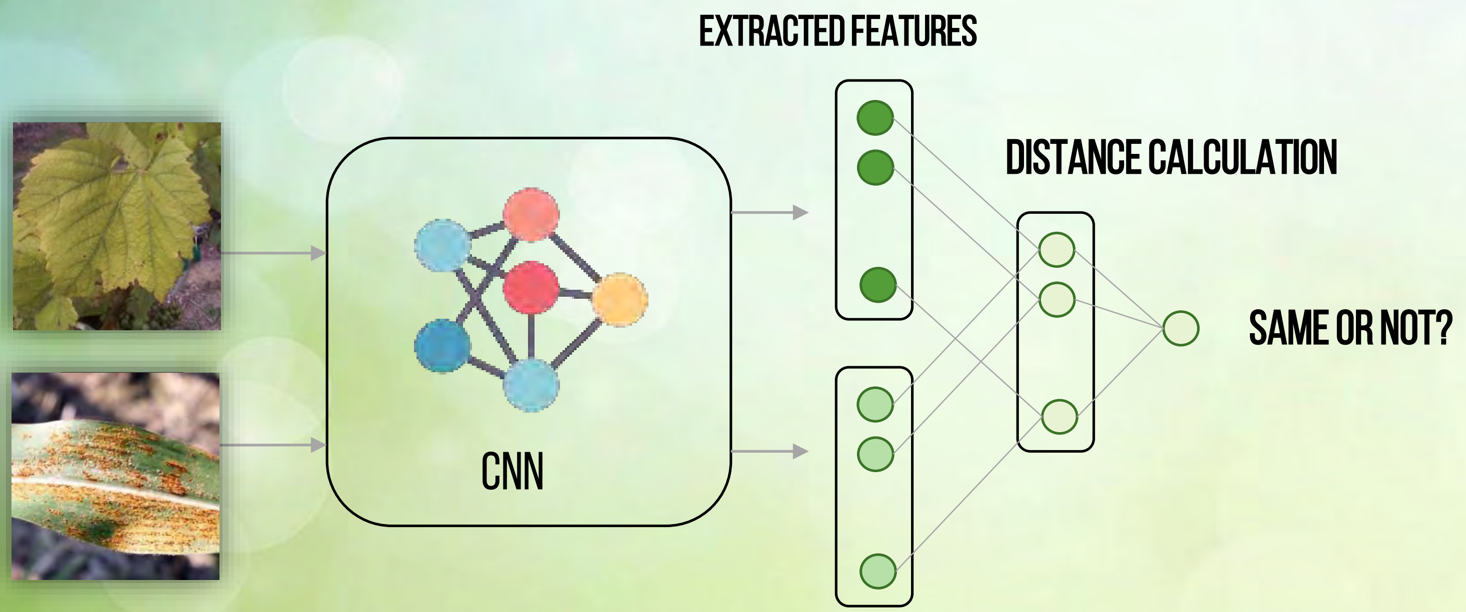
TRANSFER LEARNING



- FIND A DEEP NEURAL NETWORK PRETRAINED ON A BIG DATASET
- REPLACE THE CLASSIFICATION LAYER WITH A LAYER APPROPRIATE FOR YOUR TASK
- FINETUNE THE NEW CLASSIFIER ON SPECIFIC DATA
- VOILA! USE THE NEW MODEL FOR INFERENCE

SIAMESE NETWORKS

SIAMESE NETWORKS IS A PART OF ONE-SHOT LEARNING APPROACH. ONE SHOT-LEARNING AIMS TO LEARN INFORMATION ABOUT OBJECT CATEGORIES FROM ONE, OR ONLY A FEW, TRAINING SAMPLES/IMAGES

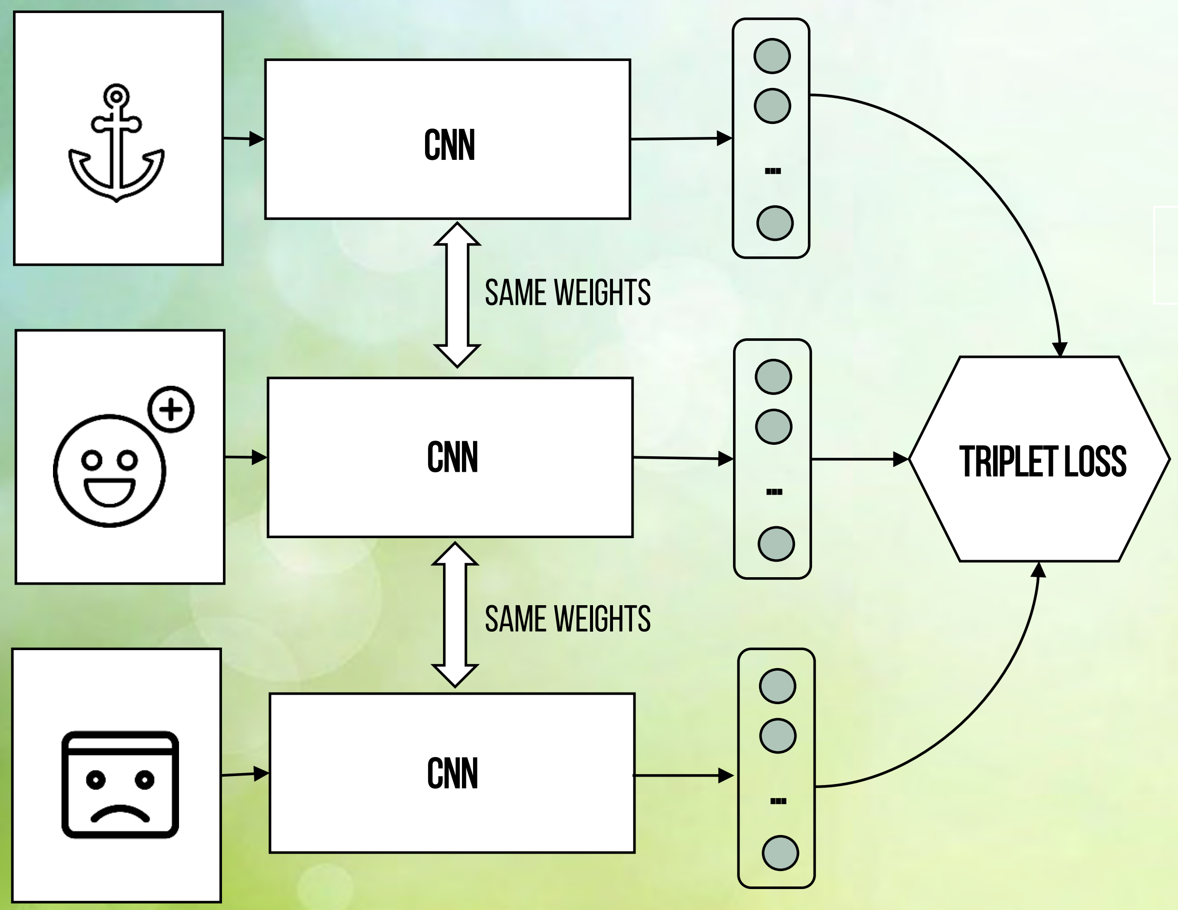


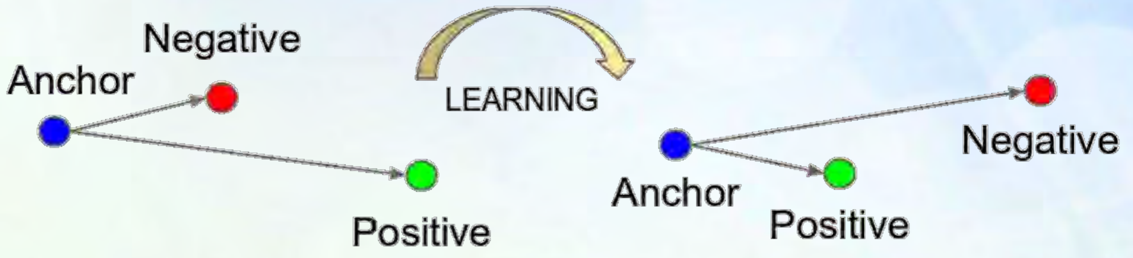
- TRAIN SIAMESE NETWORK ON YOUR OWN PAIRED DATA
- TAKE THE TRAINED TWIN AND APPEND A CLASSIFIER ON TOP OF IT
- FINETUNE THE NEW CLASSIFIER ON SPECIFIC DATA APPROPRIATE FOR YOUR TASK

SAME AS FOR TRANSFER LEARNING

https://arxiv.org/abs/1503.03832

TRIPLET NETWORKS





$$L = \max(d(a,p) - d(a,n) + margin, 0)$$

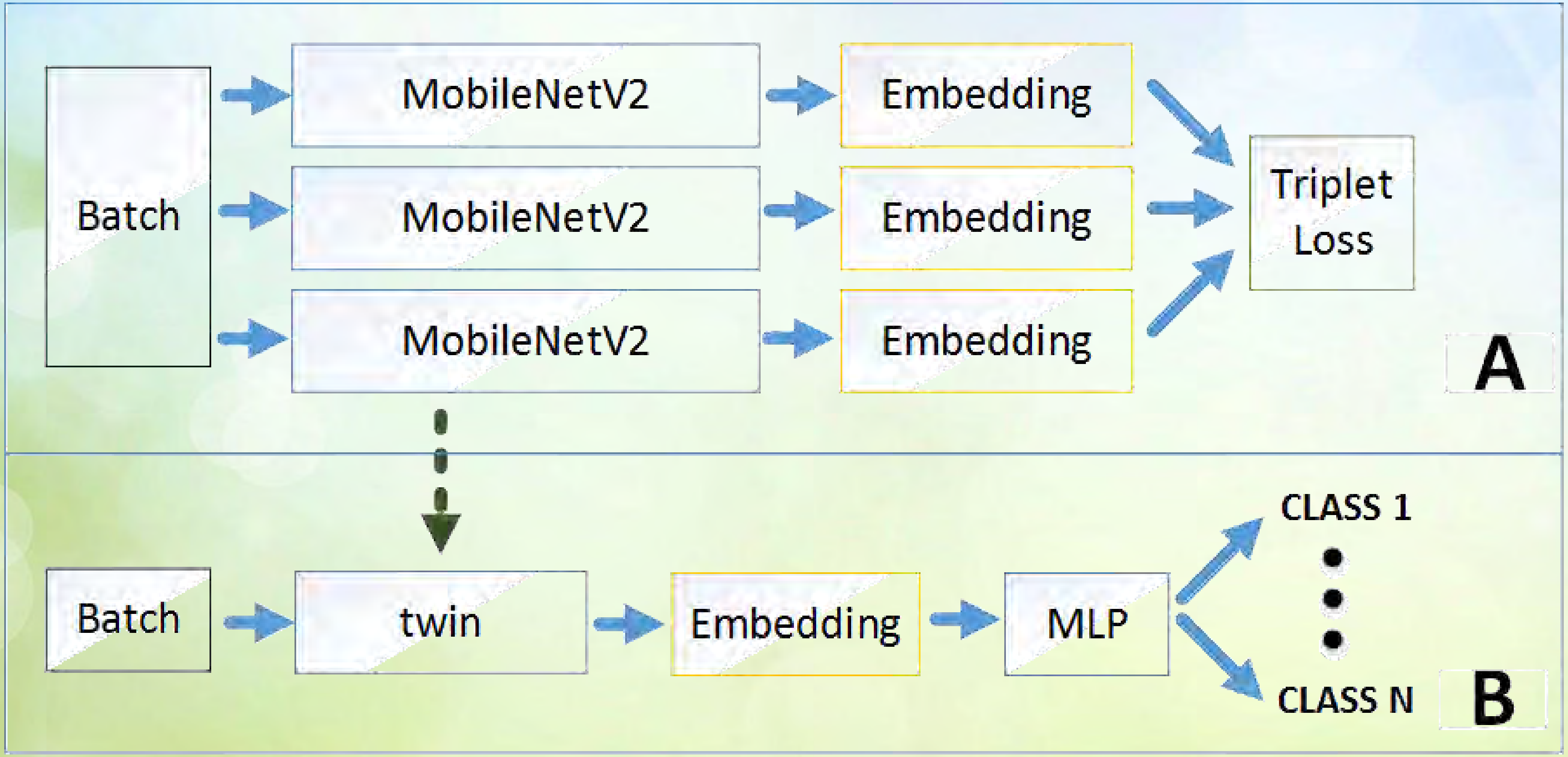
D "D" IS SOME KIND OF FUNCTION FOR CALCULATING THE DISTANCE BETWEEN VECTORS, FOR EXAMPLE, EUCLIDEAN DISTANCE.

A "A" IS AN ANCHOR IMAGE WHICH WE WANT TO IDENTIFY

P "P" IMAGE THE SAME CLASS AS ANCHOR

N "N" IMAGE OF ANOTHER CLASS NOT MATCHING THE ANCHOR

TRIPLET NETWORKS



EVALUATION RESULTS

SIMPLE CONVOLUTIONAL NEURAL NETWORK

ACCURACY LESS THAN 65%

TRANSFER LEARNING MODEL

ACCURACY LESS THAN 90%

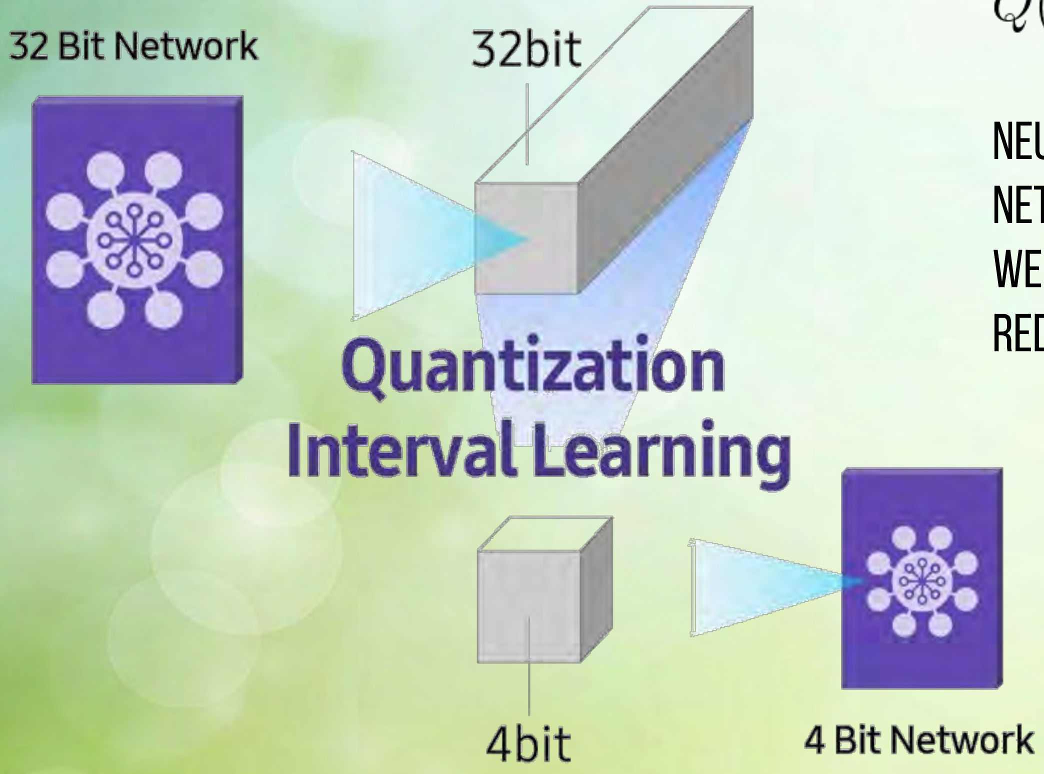
SIAMESE NETWORK

ACCURACY LESS THAN 95%

TRIPLET NETWORK

ACCURACY ~98%

QUANTIZATION: SMALLER, FASTER, BETTER?



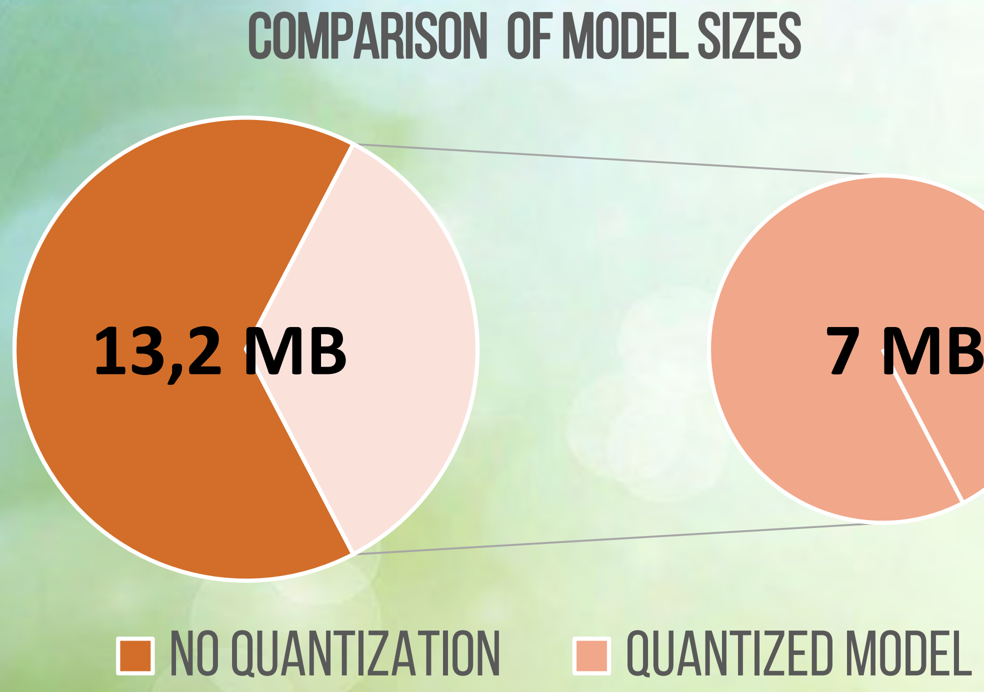
$$Q(x, \mathrm{scale}, \mathrm{zero\_point}) = \mathrm{round}\left(\frac{x}{\mathrm{scale}} + \mathrm{zero\_point}\right)$$

NEURAL NETWORKS RUN FAST ON GPU, BUT SLOW ON CPU. IN ORDER FOR THE NEURAL NETWORK MODEL TO WORK QUICKLY ON MOBILE PHONES AND ON THE WEB PORTAL, WE APPLIED THE MODEL QUANTIZATION APPROACH. THIS APPROACH ALLOWS TO REDUCE THE NUMBER OF BITS FOR DESCRIBING DATA.

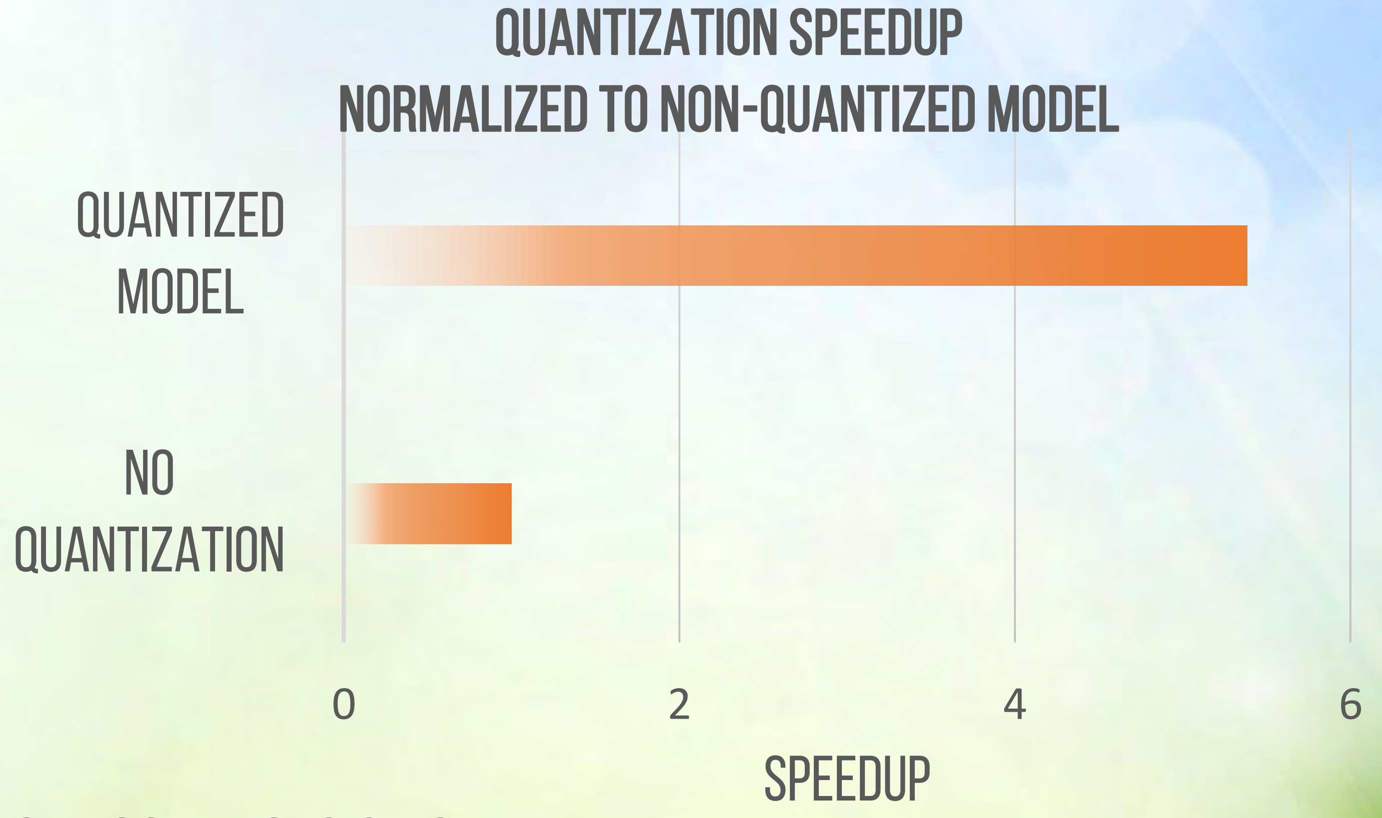
QUANTIZATION HELPS SPEED UP INFERENCE ON DEVICES:

- X86 CPUS WITH AVX2 SUPPORT OR HIGHER (WITHOUT AVX2 SOME OPERATIONS HAVE INEFFICIENT IMPLEMENTATIONS)
- ARM CPUS (TYPICALLY FOUND IN MOBILE/EMBEDDED DEVICES)

QUANTIZATION RESULTS



ACCURACY REMAINS THE SAME!



FOR 100 IMAGES ON CPU:

NO QUANTIZATION MODEL: 13.5 SEC
QUANTIZATION MODEL: 2.6 SEC

TEXT CLASSIFICATION

SOMETIMES IT IS NOT POSSIBLE TO RECOGNIZE IMAGES UPLOADED BY USERS. FOR EXAMPLE, WHEN THE IMAGES ARE OF POOR QUALITY, OR THE DISEASE IS AT AN EARLY STAGE. TO IMPROVE THE CLASSIFICATION ON THE PDDP PLATFORM, IT IS POSSIBLE TO ADD A TEXTUAL DESCRIPTION OF THE DISEASE IN ORDER TO GET A MORE ACCURATE RECOGNITION RESULT.

INPUT: «GRAPE BLACK SPOTS ON LEAFS»

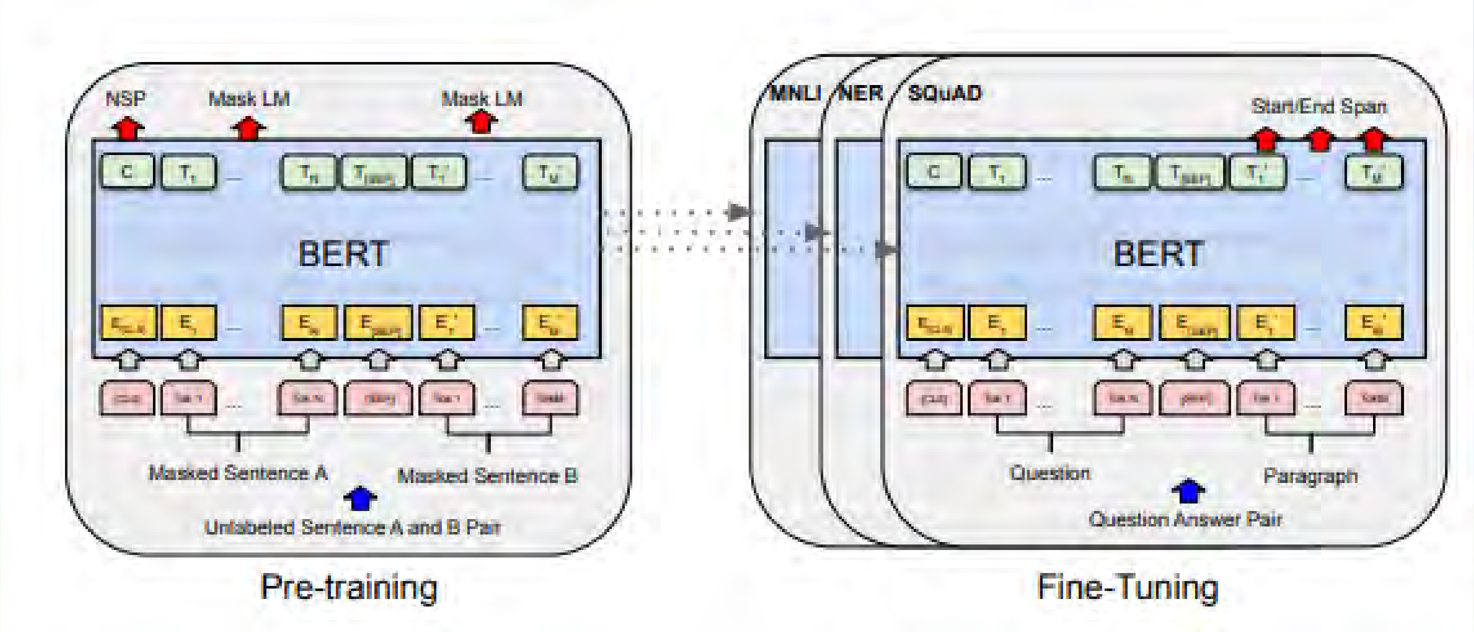
OUTPUT:

TEXT SUGGESTIONS ARE FED TO THE MODEL INPUT, AND THEY ARE CONVERTED TO VECTORS AT THE OUTPUT. THEN THESE VECTORS ARE COMPARED WITH VECTORS IN THE DATABASE OF TEXT DESCRIPTIONS OF DISEASES.

BERT MODEL

BERT MODEL WAS USED TO IDENTIFY THE DISEASE BY THE TEXT DESCRIPTION OF SYMPTOMS PROVIDED BY USERS.

BERT MODEL



- BERT IS DESIGNED TO PRETRAIN DEEP BIDIRECTIONAL REPRESENTATIONS FROM UNLABELED TEXT BY JOINTLY CONDITIONING ON BOTH LEFT AND RIGHT CONTEXT IN ALL LAYERS.
  AS A RESULT, THE PRE-TRAINED BERT MODEL CAN BE FINETUNED WITH JUST ONE ADDITIONAL OUTPUT LAYER TO CREATE STATE-OF-THE-ART MODELS FOR A WIDE RANGE OF TASKS, SUCH AS QUESTION ANSWERING

https://arxiv.org/abs/1810.04805

CONCLUSION

- WE HAVE DEVELOPED A PLATFORM FOR PLANT DISEASE RECOGNITION CONSISTING OF A WEB PORTAL AND A MOBILE APPLICATION
- COLLECTED A DATABASE OF IMAGES
- IMPLEMENTED THE TRIPLET MODEL FOR PLANT DISEASE DETECTION TRAINED ON 25 CLASSES OF FIVE CROPS SHOWS 97.8% ACCURACY.
- TRAINING STATIC QUANTIZATION WHICH ALLOWED TO REDUCE THE ORIGINAL MODEL SIZE FROM 13.2 MB TO 7 MB ALONG WITH >5 TIMES SPEEDUP OF INFERENCE WITHOUT LOSS OF ACCURACY.
- IMPLEMENTED THE TEXTUAL RECOGNITION OF PLANT DISEASES BASED ON THE BERT MODEL

OUR APPROACH HAS GREAT POTENTIAL FOR CLASSIFICATION TASKS WITH A VERY SMALL TRAINING DATASET

DEEP LEARNING IS FAT