PROJE TANITIM SUNUMU

«Trafik Gözlem Kameralarında Derin Öğrenme Yöntemleriyle Gerçek Zamanlı Video Akışı Analizi ve Kötücül Aktivite Tespiti»

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Ana Bilim Dalı Başkanı

SUNUM PLANI

1. PROJE BİLGİLERİ & LİTERATÜR ÇALIŞMALARI
2. PROJE DETAYLARI
3. YÜRÜTÜLEN ÇALIŞMALAR

PROJE BİLGİLERİ & LİTERATÜR ÇALIŞMALARI

TÜBİTAK 1005 PROJESİ

Kaynak: TÜBİTAK

1005 - Ulusal Yeni Fikirler ve Ürünler Araştırma Destek Programı

Proje No: 123E065

Proje Adı:
Trafik Gözlem Kameralarında Derin Öğrenme Yöntemleriyle Gerçek Zamanlı Video Akışı Analizi ve Kötücül Aktivite Tespiti

Proje Yürütücüsü:
Prof. Dr. Murat DENER

Proje Ekibi:
Esma DİLEK
Özgür TALİH

Proje Süresi:
18 ay
(Haziran 2023-Aralık 2024)

Proje Bütçesi:
500K TL

PROJENİN AMAÇLARI

- Trafik gözlem kameralarında derin öğrenme yöntemleriyle gerçek zamanlı video akışı analizleri ile kötücül aktivite ve olay tespitinin yapılabilmesi
- Derin öğrenme yöntemleri ile yol ağında trafik güvenliğini riske atan durumların otomatik olarak tespiti ile karayolu/otoyol işletmecilerinin olası kazaları önleyici tedbirleri hızlı bir şekilde alabilmelerinin sağlanması
- Canlı video akışlarının gerçek zamanlı olarak gelişmiş yapay zekâ teknikleri kullanılarak tespit edilebilmesi için gerekli platform oluşturulması
- İnsan gözüyle anlık tespiti zor ve zaman alıcı kötücül aktivitelerin otomatik tespit edilebilmesi
- Farklı derin öğrenme yöntemlerinin test edilerek literatürdeki çalışmalardan daha iyi sonuç elde edilebilmesine çalışılması
- Ulusal kalkınma ve strateji belgelerinde öncelik verilen yapay zekâ, büyük veri, derin öğrenme alanlarında, yerli ve milli ürünlere dönüştürülebilme kapasitesi olan bir çözüm geliştirilmesi

TRAFİK GÖZLEM KAMERALARINDA VİDEO ANOMALİ TESPİTİNİN FAYDALARI

Otoyol işletmecilerinin, trafiğin yönetiminden sorumlu yerel ve merkezi yönetimlerin karar destek süreçlerinin daha etkin işletilebilmesi

Trafikte kaybedilen zamanın azaltılması sayesinde iş gücü kaybının ve dolaylı maliyetlerin önlenmesi

Olası olumsuz durumların (ikincil kazalar, yaya/hayvan vb. canlılara zarar verilmesi vb.) önüne geçilebilmesi

Yakıt tüketiminde, sera gazı emisyonlarında düşüş kaydedilmesi ve ülke ekonomisine katkı sunulması

Video akışlarından kötücül durumların tespit edilerek efektif olay yönetimi yapılabilmesi

Çevresel olumsuz etkilerde azalma ve küresel iklim değişikliği sorununun çözümüne katkı sağlanması

Trafik kazaları ile buna bağlı ölümlerin, yaralı sayılarının ve maddi kayıpların azalması

Sağlık sorunlarının azalması ile uygulanan tedavi harcamalarının azalması ve ülke ekonomisine katkı sunulması

Trafik gözlem kameraları yardımıyla elde edilen büyük verinin analizi ile operasyonel verimliliğe katkı sunulması

ULUSAL KAZANIM & PROJENİN ÖNEMİ
Ulusal Kalkınma Planları & Stratejik Hedeflerle İlişkisi

11. Kalkınma Planı 2019-2023

2020-2023 Akıllı Şehirler Stratejisi ve Eylem Planı

Ulaştırma ve Altyapı Bakanlığı 2019-2023 Stratejik Planı

Ulusal Yapay Zekâ Stratejisi (2021-2025)

Ulusal Yapay Zekâ Stratejisi 2024-2025 Eylem Planı

Ulusal Akıllı Ulaşım Sistemleri Stratejisi Belgesi ve 2020-2023 Eylem Planı

Yeşil Mutabakat Eylem Planı (2021)

Mobilite Araç Teknolojileri Strateji Yol Haritası (2022)

2023 Sanayi ve Teknoloji Stratejisi

12. Kalkınma Planı 2024-2028

LİTERATÜR ÇALIŞMALARI

Ref.	Yıl	Yazar	Yöntem	VeriSetleri		
				CUHK Avenue [5]	UCSD Ped1 [6]	UCSD Ped2 [6]
[51]	2015	Yan et al.	Two-Stream R-ConvVAE	79.6%	75.0%	91.7%
[52]	2016	Hasan et al.	ConvAE	70.2%	81.0%	90.0%
[50]	2016	Zhang et al.	Method based on locality sensitive hashing filters	N/A*[]	87.0%	91.0%
[53]	2016	Colque et al.	HOF (Histogram of Optical Flow)	N/A	72.7%	87.5%
[30]	2017	Chong &Tay	ST-AE	80.3%	89.9%	87.4%
[31]	2017	Lu et al.	ConvLSTM-AE	77.0%	75.5%	88.1%
[54]	2017	Zhao et al.	3D-ConvAE	80.9%	92.3%	91.2%
[55]	2017	Ionescu et al.	Unmasking	80.6%	68.4%	82.2%
[37]	2017	Luo et al.	sRNN (Stacked RNN)	81.7%	N/A	92.2%
[56]	2017	Sun & Liu	GrowingGas	N/A	93.8%	94.1%
[31]	2017	Luo et al.	LSTM-AE	77%	75.5%	88.1%
[57]	2018	Lee et al.	STAN	87.2%	82.1%	96.5%
[58]	2018	Yang et al.	WCAE-LSTM	85.7%	85.1%	92.6%
[59]	2018	Riberio et al.	Conv-AE	77.2%	58.5%	84.7%
[60]	2018	Kiran et al.	CovnLSTM-AE	84%	74%	81%
[10]	2018	Liu et al.	Flownet + U-Net	85.1%	83.1%	95.4%

Ref.	Yıl	Yazar	Yöntem	VeriSetleri		
				CUHK Avenue [5]	UCSD Ped1 [6]	UCSD Ped2 [6]
[61]	2018	Xu et al.	ICN (Intra-frame Network)	N/A	82.0%	90.2%
[62]	2018	Xu et al.	SVM (Support Vector Machie)	N/A	94.1%	89.2%
[63]	2018	Wang et al.	Two-stage (Histograms of the orientation of optical flow descriptor + one-class SVM)	85.3%	77.8%	96.4%
[64]	2018	Wang et al.	S^2 -VAE	87.6%	94.25%	N/A
[10]	2018	Liu et al.	FFP (Future Frame Prediction)	85.1%	83.1%	95.4%
[65]	2019	Chu et al.	Sparse Coding Guided Spatiotemporal Feature Learning (SCG-SF)	82.1%	90.6%	90.2%
[66]	2019	Duman & Erdem	OF-ConvAE-LSTM	89.5%	92.4%	92.9%
[67]	2019	Li et al.	U-Net, ConvLSTM	84.5%	83.8%	96.5%
[16]	2019	Zhou et al.	AnomalyNet	86.1%	83.5%	94.9%

LİTERATÜR ÇALIŞMALARI

Ref.	Yıl	Yazar	Yöntem	VeriSetleri		
				CUHK Avenue [5]	UCSD Ped1 [6]	UCSD Ped2 [6]
[68]	2019	Song et al.	GAN (Generative Adversarial Network)	89.2%	90.5%	90.7%
[69]	2019	Wu et al.	DeepOC (Deep One Class Neural Network)	88.6%	83.5%	96.9%
[70]	2019	Vu et al.	MLAD (MultiLevel Anomaly Detector)	52.82%	82.34%	99.21%
[71]	2019	Gong et al.	memAE (memory-augmented autoencoder)	83.3%	N/A	94.1%
[72]	2019	Ye et al.	AnoPCN	86.2%	N/A	96.8%
[73]	2019	Nguyen & Meunier	AMC (Appearance-Motion Correspondence)	86.9%	N/A	96.2%
[74]	2019	Lu et al.	VAE + ConvLSTM	85.78%	86.26%	96.06%
[75]	2020	Deepak et al.	R-STAE (Residual STAE using 3D CONVLSTM)	82%	N/A	83%
[76]	2020	Chen et al.	U-Net	87.8%	89%	96.6%
[77]	2020	Nawaratne et al.	ISTL (Incremental Spatiotemporal Learner)	76.8%	75.2%	91.1%

Ref.	Yıl	Yazar	Yöntem	VeriSetleri		
				CUHK Avenue [5]	UCSD Ped1 [6]	UCSD Ped2 [6]
[78]	2020	Sun et al.	Adversarial 3D Autoencoder	88.9%	90.2%	91.1%
[79]	2020	Bansod & Nandedkar	HoMM (Histogram of Magnitude and Momentum)	N/A	82.31%	94.16%
[80]	2020	Ganokratanaa et al.	DSTN (Deep Spatiotemporal Translation Network based on GAN and Edge Wrapping (EW))	87.9%	**98.5%**	95.5%
[81]	2020	Cho et al.	ITAE + NFs (Implicit two-	85.8%	N/A	97.3%
[82]	2020	Yu et al.	VEC (Video Event Completion - Cloze Test)	89.6%	N/A	97.3%
[83]	2020	Dong et al.	Dual discriminator-based GAN	84.9%	N/A	95.6%
[84]	2020	Li et al.	ST-CaAE (Spatial-temporal cascade autoencoder)	83.5%	90.5%	92.9%

LİTERATÜR ÇALIŞMALARI

Ref.	Yıl	Yazar	Yöntem	VeriSetleri		
				CUHK Avenue [5]	UCSD Ped1 [6]	UCSD Ped2 [6]
[43]	2020	Shin et al.	3D-CNN with GAN and AE	N/A	95%	93%
[82]	2020	Yu et al.	CTH (Cloze test helps)	89.6%	N/A	97.3%
[85]	2020	Tang et al.	IPR (Future Frame Prediction + Reconstruction)	83.7%	82.6%	96.2%
[86]	2020	Zhou et al.	Attention-Prediction	86.0%	83.9%	96.0%
[87]	2020	Lu et al.	r-GAN	85.3%	83.7%	95.9%
[88]	2020	Park et al.	MNAD (Memory-guided Normality for Anomaly Detection)	88.5%	N/A	97%
[89]	2020	Chang et al.	CDDAE (Clustering Driven Deep Autoencoder)	86%	N/A	96.5%
[90]	2020	Doshi & Yılmaz	transfer learning + continual learning	89.6%	N/A	97.8%
[91]	2021	Saypadith & Onoye	Multi-scale U-Net (GAN-Deep Generative Network)	86.9%	85.3%	95.7%
[20]	2021	Samuel & Cuzzolin	SVD-GAN (Singular Value Decomposition GAN)	89.82 %	73.26%	76.98%

Ref.	Yıl	Yazar	Yöntem	VeriSetleri		
				CUHK Avenue [5]	UCSD Ped1 [6]	UCSD Ped2 [6]
[99]	2021	Liu et al.	HF^2-VAD (Hybrid framework that integrates Flow reconstruction + Frame prediction)	91.1%	N/A	**99.3%**
[100]	2021	Cai et al.	AMMC-Net (Appearance-Motion Memory Consistency Network)	86.6%	N/A	96.6%
[101]	2022	Sabih & Vishwakarma	CNN + Bi-LSTM	N/A	94.8%	96.5%
[115]	2022	Guo et al.	Self-training	86.6%	74.7%	88.1%
[116]	2022	Zhang et al.	NUFP (Non-local U-Net frame prediction)	85.2%	83.6%	95.9%
[117]	2022	Hao et al.	STCEN (Spatiotemporal consistency-enhanced network)	86.6%	82.5%	96.9%
[118]	2023	Sun et al.	FTS-LSTM (feature trajectory–smoothed LSTM)	91.1%	83.5%	98.3%

LİTERATÜR ÇALIŞMALARI

Ref.	Yıl	Yazar	Yöntem	VeriSetleri		
				CUHK Avenue [5]	UCSD Ped1 [6]	UCSD Ped2 [6]
[114]	2022	Chang et al.	STD (spatio-temporal dissociation)	87.1%	N/A	96.7%
[115]	2022	Guo et al.	Self-training	86.6%	74.7%	88.1%
[116]	2022	Zhang et al.	NUFP (Non-local U-Net frame prediction)	85.2%	83.6%	95.9%
[117]	2022	Hao et al.	STCEN (Spatiotemporal consistency-enhanced network)	86.6%	82.5%	96.9%
[118]	2023	Sun et al.	FTS-LSTM (feature trajectory–smoothed LSTM)	91.1%	83.5%	98.3%
[119]	2023	Li et al.	Multi-memory video anomaly detection algorithm	84.34%	N/A	96.75%
[120]	2023	Li et al.	ACP-VAD (Adversarial composite prediction)	88.7%	N/A	96.8%
[121]	2023	Wang et al.	STR-VAD (spatio-temporal relationships)	86.1%	N/A	98.4%
[122]	2023	Gayal & Patil	HiS-Deep CNN (hierarchical-based social hunting optimization tuned Deep-CNN)	83.04%	74.73%	79.54%

Ref.	Yıl	Yazar	Yöntem	VeriSetleri		
				CUHK Avenue [5]	UCSD Ped1 [6]	UCSD Ped2 [6]
[144]	2023	Taghinezhad ve Yazdi	MsMp-Net (Multi-Scale Feature Memorization and Multipath Network)	89	83,8	97,6
[145]	2023	Li vd.	Double-Canny algorithm + YoloV4	85,9	-	95,9
[146]	2023	Aslam ve Kolekar	DeMAAE (Deep Multiplicative Attention-Based Autoencoder)	83,4	90,7	96,2
[147]	2023	Sophia ve Chitra	PFPN-ADT (Panoptic Feature Pyramid Network based Anomaly Detection and Tracking)	-	92,35	94,23
[148]	2023	Astrid vd.	PseudoBound (Pseudo Anomaly-based Training)	87,10	-	98,44
[149]	2023	Zhou vd.	Memory-guided Multilevel Embedding	87,6	-	97,8
[150]	2023	Zeng vd.	HSTGCNN (Hierarchical Spatio-Temporal Graph Convolutional Neural Network)	87,51	83,39	97,73
[151]	2023	Sun ve Yang	Multi-timescale Trajectory Prediction (YOLOv5 + DeepSort)	92,8	-	-
[152]	2023	Zhang vd.	Attention Mechanism	85,9	80,5	97,9
[153]	2023	Wang ve Chen	DSM-Net (Dual-Stream Memory Network)	88,6	-	98,3
[154]	2024	Dilek ve Dener	TL-FT-Based VAD	98,41	**100**	**100**
[74]	2024	Niaz vd.	C3DN_AE_Fusion (Convolutional 3D Autoencoder Fusion)	84,7	94,6	96,7

LİTERATÜR ÇALIŞMALARINDAN FARKI & MOTİVASYON

Mevcut Durum & İhtiyaçlar

- Literatür çalışmalarında video gözlem kameralarından anomali tespitine yönelik yapılan araştırmalarda, ağırlıklı olarak kamuya açık kıyaslama veri setleri kullanılmıştır.
- Bu veri setlerinde başarı performansını yükseltmek için farklı yöntemlerden yararlanılmıştır.

- Gerçek zamanlı işleme için uygun video anomali tespit yöntemlerinde eksiklik bulunmaktadır.
- Literatürde tespit doğruluğu ile hesaplama karmaşıklığı arasındaki dengeye fazla dikkat edilmemiştir.

PROJE DETAYLARI

PROJENİN KAPSAMI

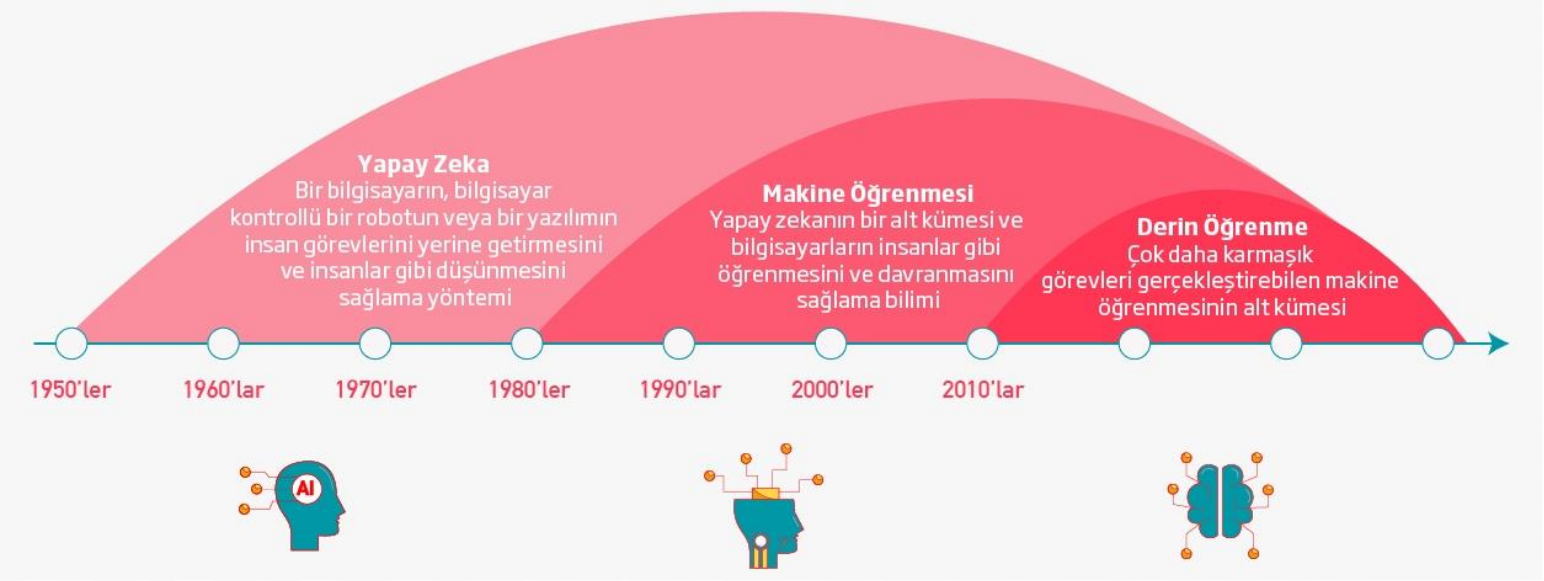
KMO güzergahındaki trafik gözlem kamera görüntülerini kullanarak **hibrit derin öğrenme yöntemleriyle canlı video akışlarının analiz edilmesi, gerçek zamanlı kötücül aktivite tespiti**

Literatür çalışmaları ve örnek veri setleri göz önünde bulundurularak proje kapsamında **kötücül aktivite tespitine ilişkin kapsamın belirlenmesi**

TÜBİTAK TRUBA e-altyapısında farklı **hibrit yöntemler**i deneyerek akıllı ulaşım ve akıllı şehir projelerinde yararlanılabilecek **derin öğrenme tabanlı yapay zeka modeli** geliştirilmesi, başarısının ölçülmesi

Yerli teknoloji geliştirici firmalarla ticari bir ürüne dönüştürülebilmesi için **iş birliği** fırsatlarının oluşturulması

YÖNTEM
Hibrit Derin Öğrenme



Makine Öğrenmesi → **Yapay Sinir Ağları** → **Derin Öğrenme**

PLANLANAN ÇALIŞMALAR

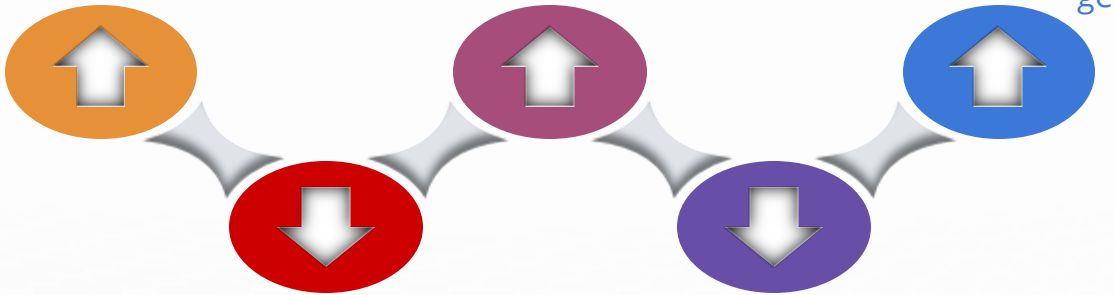
1. Gerçek zamanlı video akışlarının analiz edilebileceği platform, derin öğrenme yöntemlerinin geliştirilebileceği, test edilebileceği geliştirme ortamları oluşturulması
2. Geliştirilecek modelin, yapay zekâ uygulamaları için tasarlanmış, GPU kartlara sahip makinalar üzerinde çalıştırılması
3. Trafik gözlem kameralarında görüntü işleme tekniklerinin kullanılmasını konu alan literatür çalışmaları göz önünde bulundurularak proje kapsamında video anomali tespitine ilişkin çerçevenin oluşturulması
4. GAN (Generative Adversarial Network), GRU (Gated Recurrent Unit), LSTM (Long Short Term Memory), MobileNet, EfficientNet, YOLO (You Only Look Once), Transfer Learning gibi derin öğrenme teknikleri denenek daha iyi performans sunan hibrit model ve yöntemler geliştirilmesi
5. Trafik gözlem kameralarında canlı video akışı analizi ve kötücül aktivitelerin tespitinin yapılması
6. Literatürde yaygın olarak tercih edilen performans ölçüm metrikleri (AUC, ROC eğrisi, Doğruluk vb.) kullanılarak geliştirilen modelin başarısının ölçülmesi

PROJE KAPSAMINDAKİ İŞLER

İhtiyaca uygun donanım ihtiyaçlarının tedarik edilerek gerekli yazılım ve sistem bileşenlerinin kurulması

Gerekli örnek veri setlerinin tedarik edilmesi ve çalışma için uygun hale getirilmesi

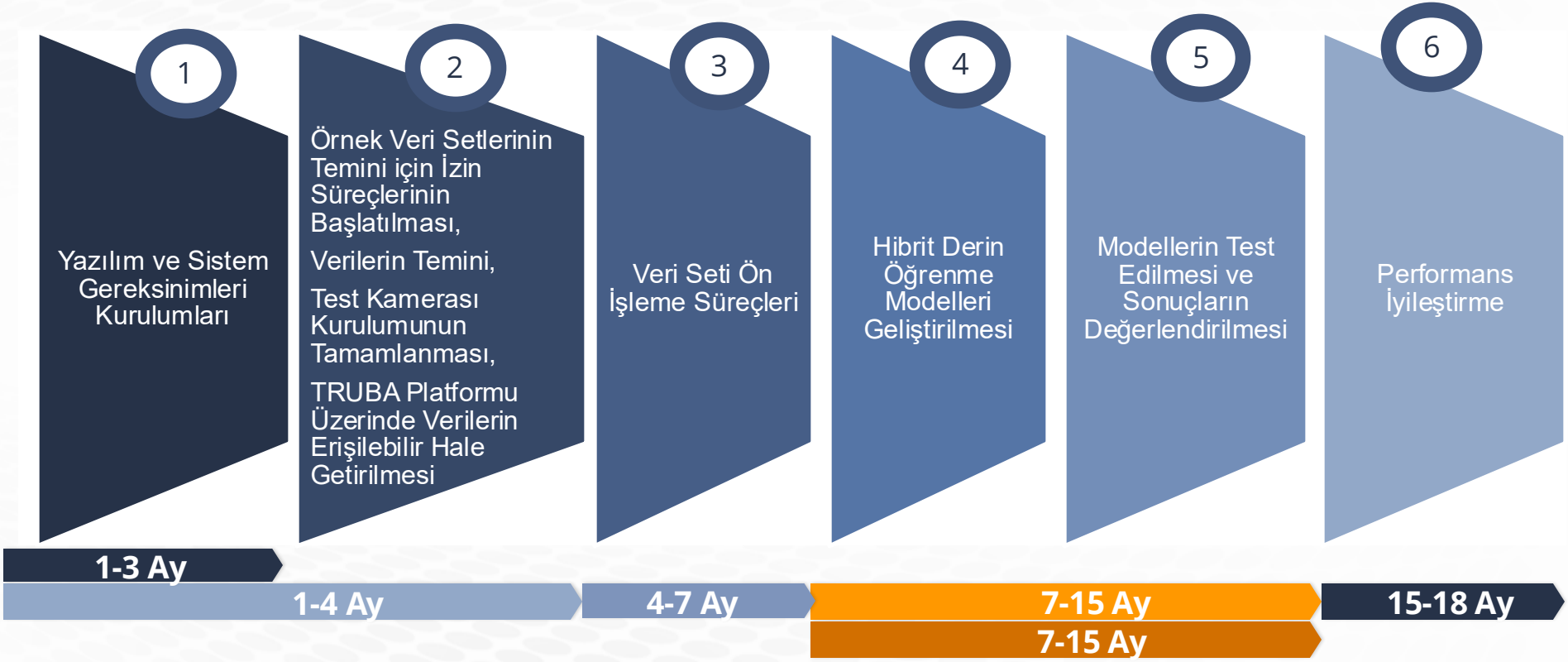
Yazılım ve sistem gereksinimlerinin kurulumları, yazılım geliştirme aşamasına geçilerek derin öğrenme tabanlı canlı video analiz yöntemi geliştirilmesi



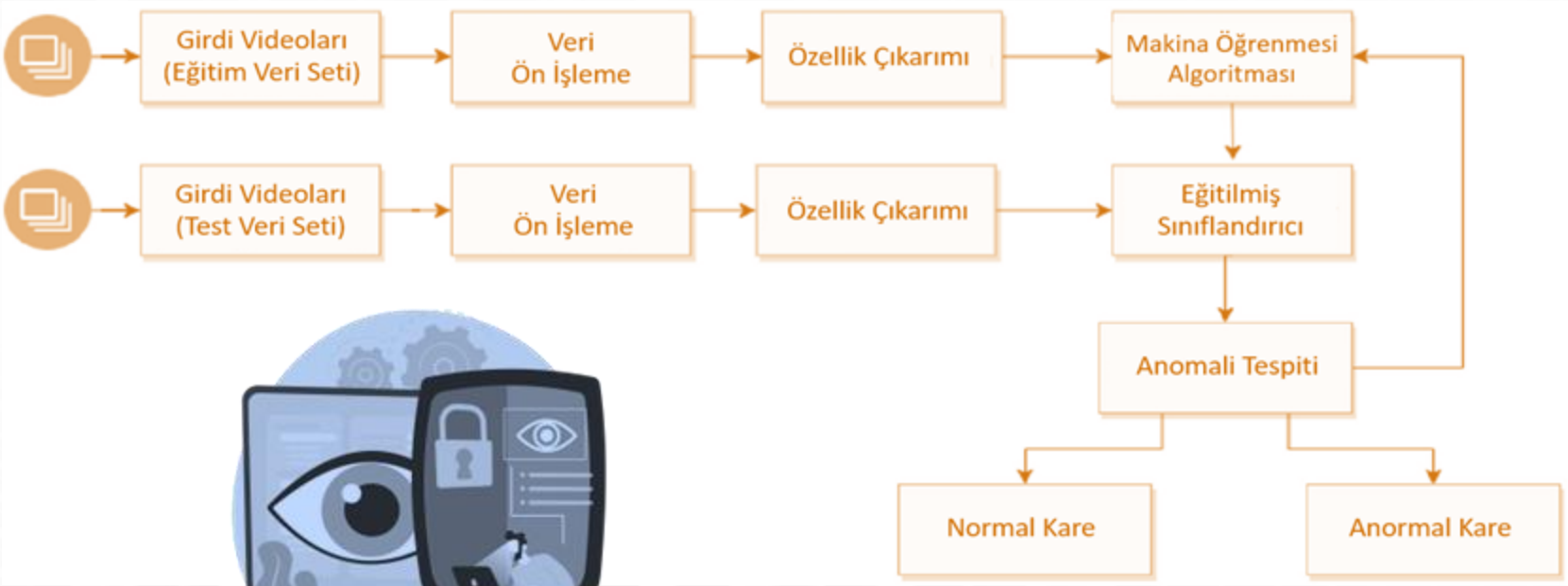
Örnek veri setleri ile testler gerçekleştirilerek geliştirilen yöntemin başarısı ölçülmesi

Çalışma performansının iyileştirilmesi için yapay zekâ tabanlı farklı hibrit yöntemler denenmesi

İŞ PAKETLERİ



VİDEO GÖZLEM KAMERALARINDA ANOMALİ TESPİTİ



KULLANILAN ARAÇLAR

HEDEFLENEN ÇIKTILAR

Araştırmacı Yetiştirilmesine Yönelik Çıktılar

Proje konusunu adresleyen Esma DİLEK'in Doktora Tez çalışması ile Özgür TALİH'in Yüksek Lisans Tez çalışmalarına katkı sunulması hedeflenmektedir.

Ekonomik/Ticari/Sosyal Çıktılar

Gerçek zamanlı video anomali tespiti yapabilen ve trafik kontrol merkezlerinde kullanılan yerli yazılımlara entegrasyonu mümkün bir yapay zekâ modeli geliştirilmesi planlanmaktadır.

Bilimsel/Akademik Çıktılar

Canlı video akışlarının analiz edilerek kötücül aktivite tespitine imkân sağlayacak bir yöntem geliştirilmesi, literatüre katkı sunması hedeflenmektedir.
SCI indeksli bir makale ve **bir konferans bildirisi** yayınlanması planlanmıştır.

PROJE ÇIKTILARININ PAYLAŞIMI & YAYILIMI

Uluslararası AUS Zirvesi

Ulusal AUS Platformu

AUS Türkiye Bülteni

AUS Türkiye Webinarı

GitHub

AUS Türkiye & SUMMITS Web Sitesi

Proje Tanıtım Toplantısı

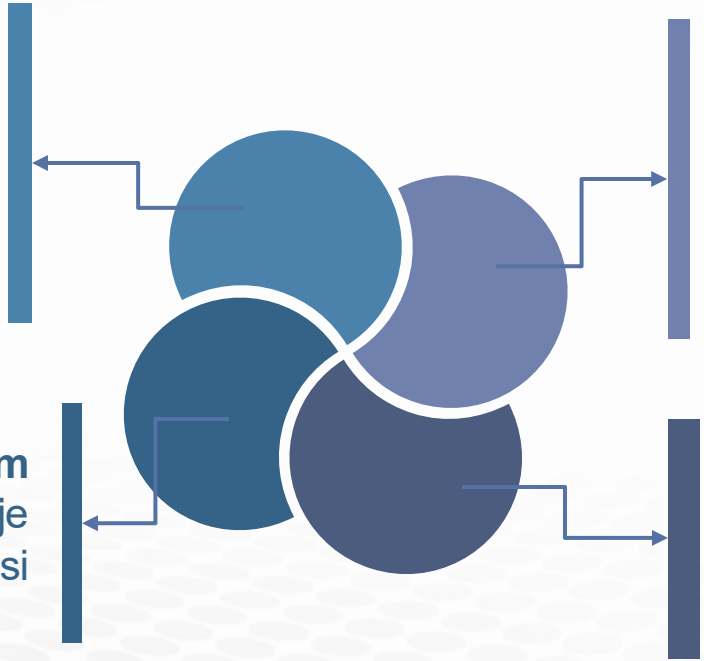
"Trafik gözlem videolarının bilgisayar destekli akıllı sistemler ile analizi sayesinde, görüntüler üzerindeki değerlendirmelerde bilgisayar kontrolü ve verilerin doğruluğunun artırılarak insan kaynaklı hata payının azaltılması, **ülke ekonomisine katkı sağlanması hedeflenmiştir.**"

YÜRÜTÜLEN ÇALIŞMALAR

İŞ PAKETİ 1 (1-3 Ay)
Yazılım ve Sistem Gereksinimleri Kurulumları

Web sunucusunun tedarik edilmesi, gerekli yazılım ve sistem bileşenlerinin kurularak yapılandırılması

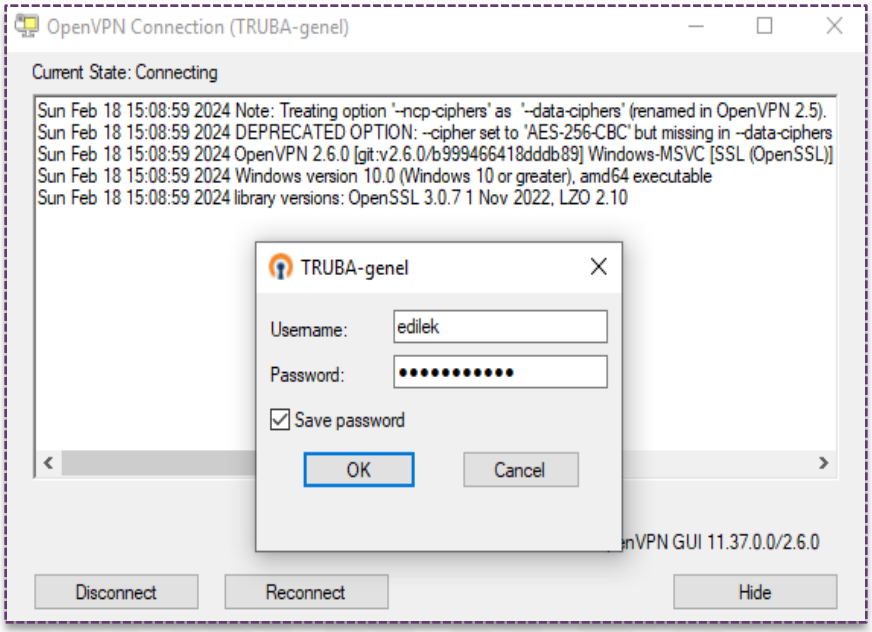
TRUBA ortamında yapay zeka (AI) modeli geliştirebilmek için gerekli konfigürasyon ayarlarının yapılması, kütüphanelerin kurulumu

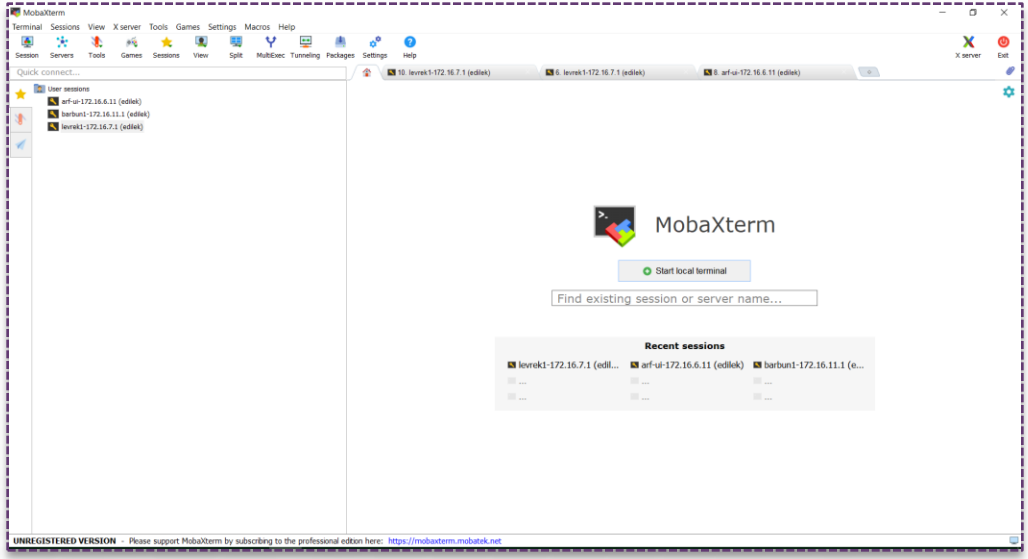


TRUBA ortamına erişim için gerekli kullanıcı/proje hesap bilgilerinin edinilmesi

TRUBA ortamında örnek AI modeli oluşturularak test edilmesi

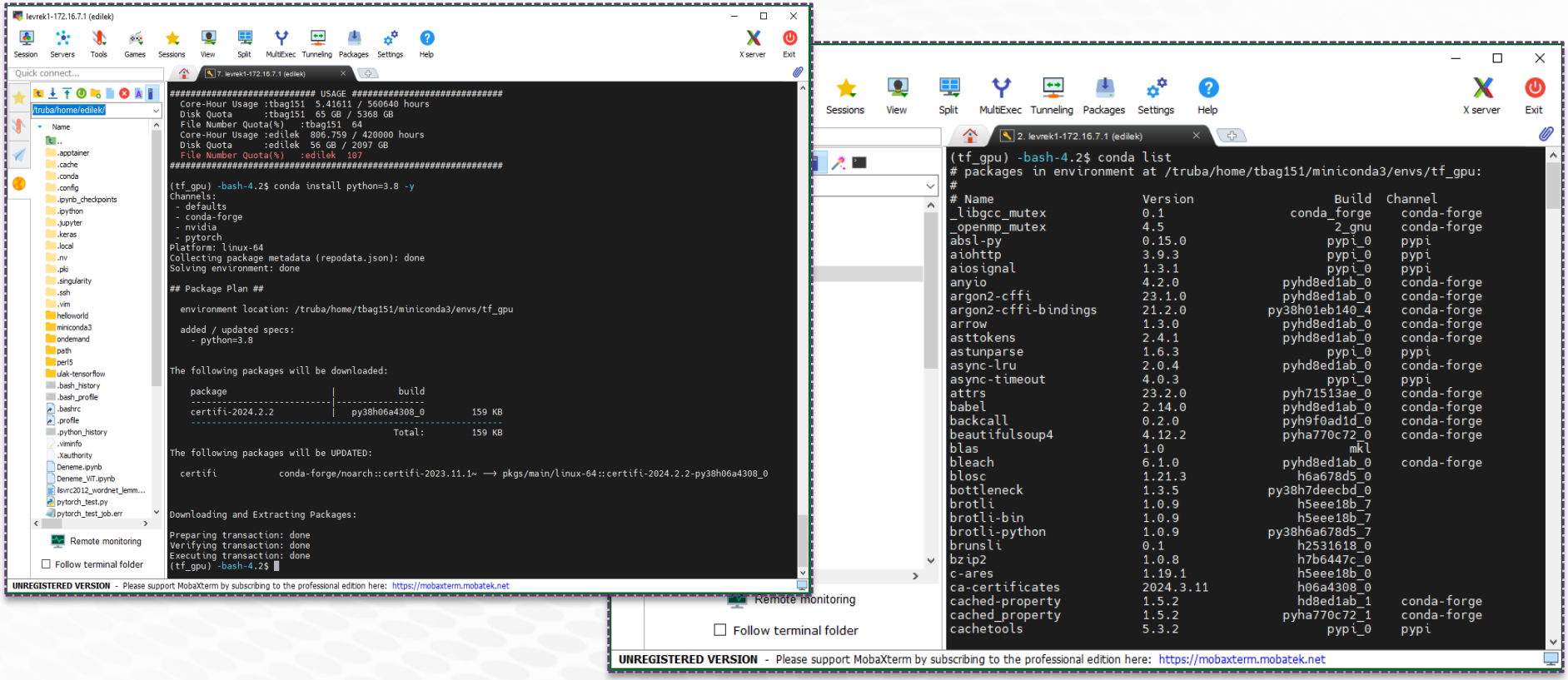
İŞ PAKETİ 1 (1-3 Ay)
Yazılım ve Sistem Gereksinimleri Kurulumları



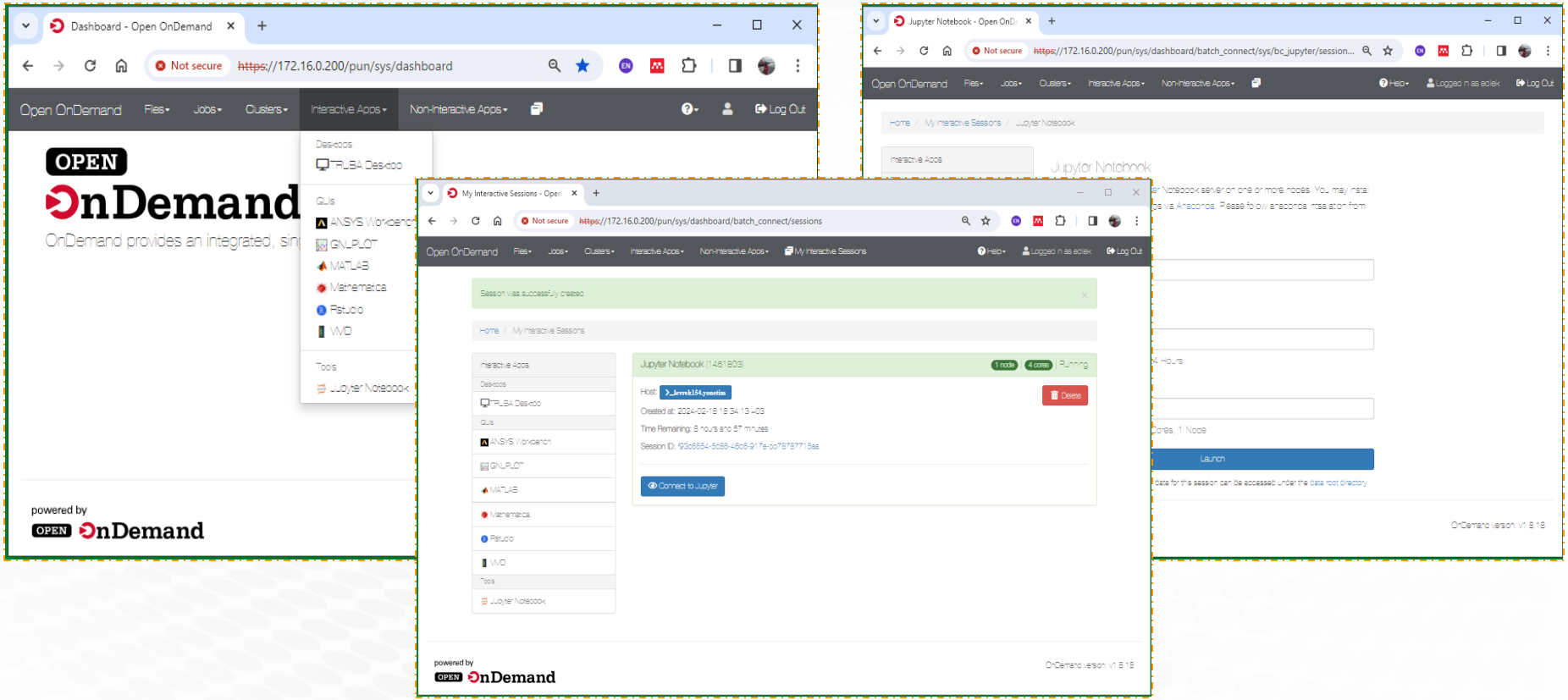


İŞ PAKETİ 1 (1-3 Ay)

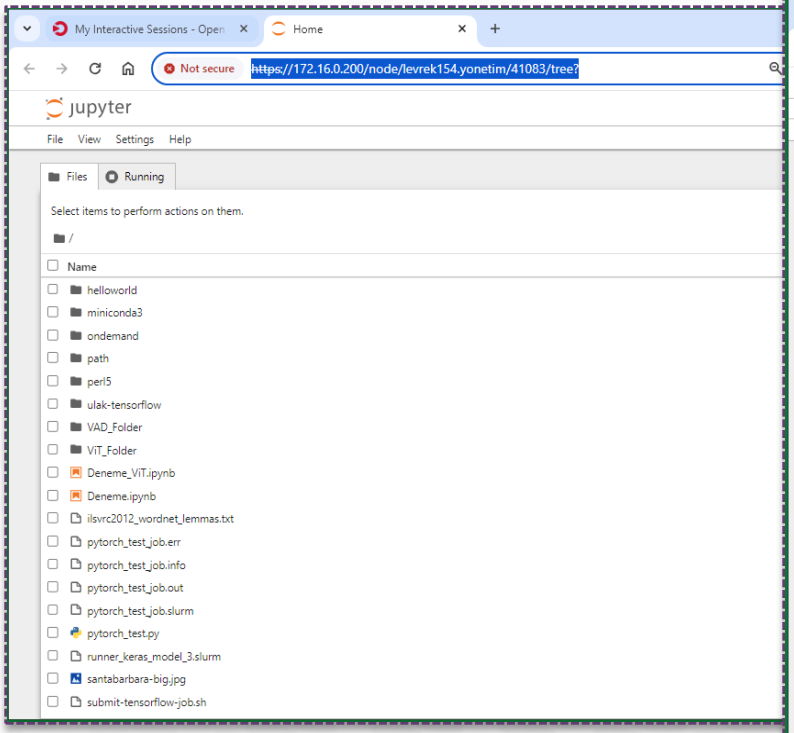
Yazılım ve Sistem Gereksinimleri Kurulumları

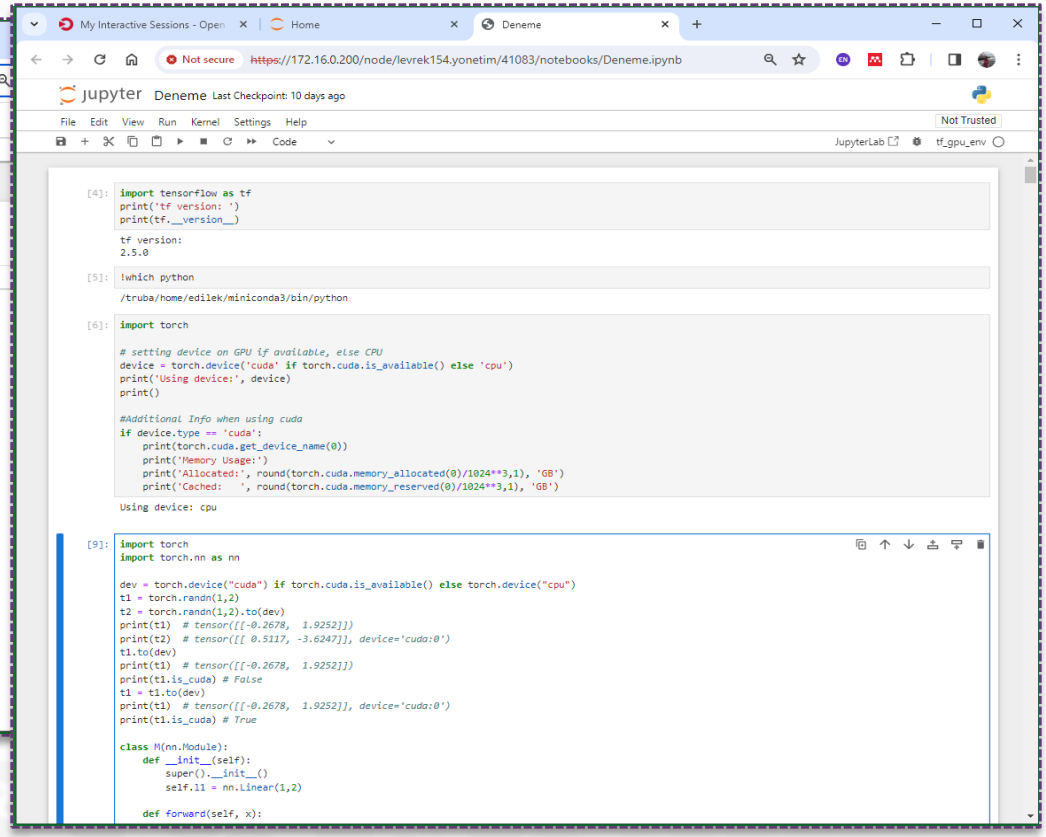


İŞ PAKETİ 1 (1-3 Ay)
Yazılım ve Sistem Gereksinimleri Kurulumları



İŞ PAKETİ 1 (1-3 Ay)
Yazılım ve Sistem Gereksinimleri Kurulumları





İŞ PAKETİ 1 (1-3 Ay)
Yazılım ve Sistem Gereksinimleri Kurulumları

MobaTextEditor

File Edit Search View Format Encoding Syntax Special Tools

tf_print_gpu.py

```
import tensorflow as tf
print('tf version: ')
print(tf.__version__)

import os
os.environ['TF_XLA_FLAGS'] = '--tf_xla_enable_xla_devices'

print("GPUs: ", len(tf.config.experimental.list_physical_devices('GPU')))

from tensorflow.python.client import device_lib
print("Local Devices:", device_lib.list_local_devices())

print('GPU List: ')
print(tf.config.list_physical_devices('GPU'))

strategy = tf.distribute.MirroredStrategy()

print("Number of devices: {}".format(strategy.num_replicas_in_sync))

import atexit
atexit.register(strategy._extended._collective_ops._pool.close)
```

C:\Users\UB10709\AppData\Roaming\MobaXterm\slash\RemoteFil UNIX Python 22 lines

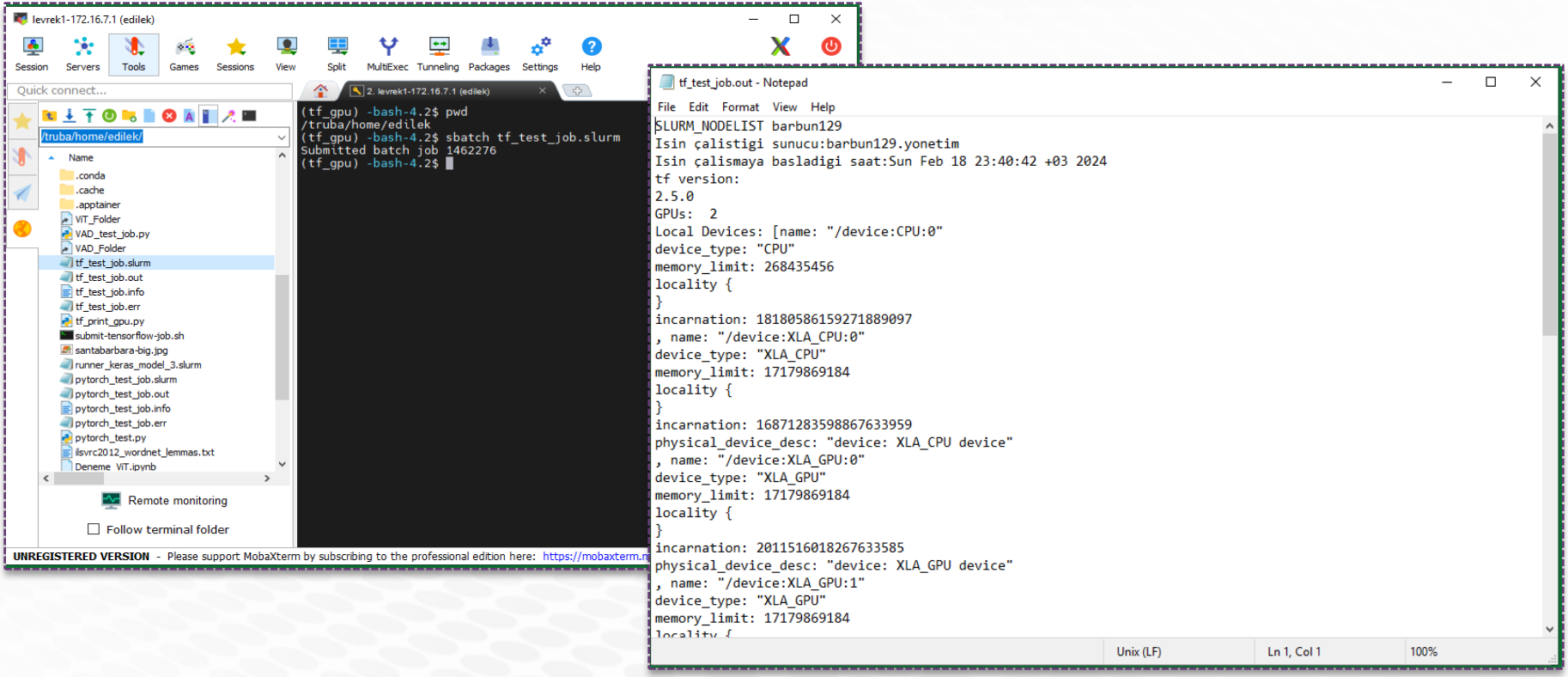
tf_test_job.slurm - Notepad

File Edit Format View Help

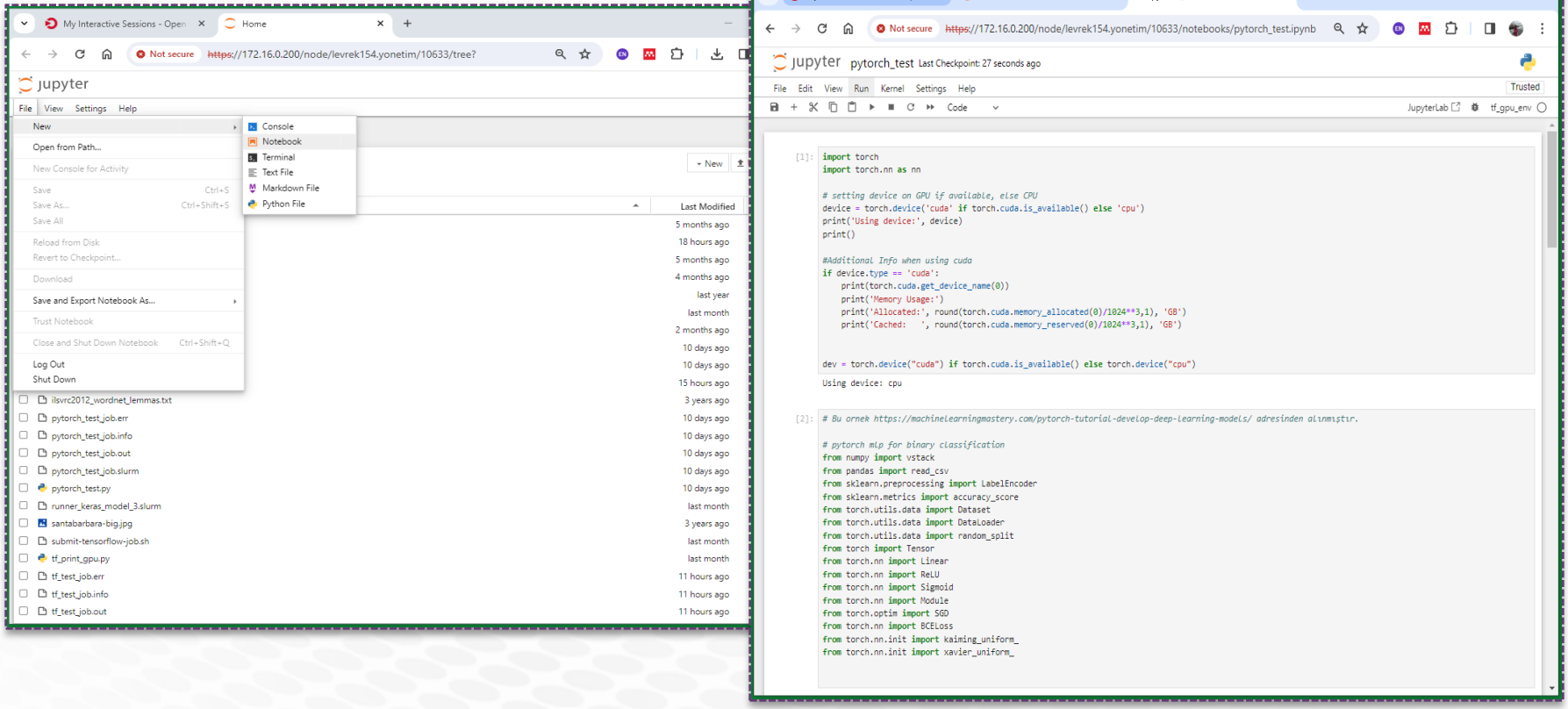
```
#!/bin/bash
#SBATCH -A edilek
#SBATCH -p debug # Debug=15 dk, Short=4 saat, Mid1=4 gun, Mid2=8 gun
#SBATCH -C barbun-cuda
#SBATCH -J tf_test_job # Gonderilen isin ismi
#SBATCH -o tf_test_job.out    # Ciktinin yazilacagi dosya adi
#SBATCH --error=tf_test_job.err # Hatanin yazilacagi dosya adi
#SBATCH -N 1 # Gorev kac node'da calisacak?
#SBATCH -n 1 # Ayni gorevden kac adet calistirilacak?
#SBATCH -c 4 # her bir gorev icin kullanilacak cekirdek adedi, varsayilan=1
# is icin talep edilen toplam cekirdek adedi = n x c

#SBATCH --time=00:02:00 #varsayilan sure 2dk

echo "SLURM_NODELIST $SLURM_NODELIST"
echo -n "Isin çalistigi sunucu:"
hostname

echo -n "Isin çalismaya basladigi saat:"
date

python tf_print_gpu.py

echo -n "Isin sonlandigi saat:"
date

scontrol show job $SLURM_JOB_ID >> tf_test_job.info
exit
```

Unix (LF) Ln 28, Col 5 100%

İŞ PAKETİ 1 (1-3 Ay)
Yazılım ve Sistem Gereksinimleri Kurulumları



İŞ PAKETİ 1 (1-3 Ay)
Örnek Yapay Zeka Modeli Geliştirilmesi



İŞ PAKETİ 1 (1-3 Ay)
Örnek Yapay Zeka Modeli Geliştirilmesi

MobaTextEditor

File Edit Search View Format Encoding Syntax Special Tools

pytorch_test.py

```python
import torch
import torch.nn as nn

# setting device on GPU if available, else CPU
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print('Using device:', device)
print()

#Additional Info when using cuda
if device.type == 'cuda':
    print(torch.cuda.get_device_name(0))
    print('Memory Usage:')
    print('Allocated:', round(torch.cuda.memory_allocated(0)/1024**3,1), 'GB')
    print('Cached:   ', round(torch.cuda.memory_reserved(0)/1024**3,1), 'GB')


dev = torch.device("cuda") if torch.cuda.is_available() else torch.device("cpu")

# Bu ornek https://machinelearningmastery.com/pytorch-tutorial-develop-deep-learning-models/ adresinden alinmistir
# pytorch mlp for binary classification
from numpy import vstack
from pandas import read_csv
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
from torch.utils.data import Dataset
from torch.utils.data import DataLoader
from torch.utils.data import random_split
from torch import Tensor
from torch.nn import Linear
from torch.nn import ReLU
from torch.nn import Sigmoid
from torch.nn import Module
from torch.optim import SGD
from torch.nn import BCELoss
from torch.nn.init import kaiming_uniform_
from torch.nn.init import xavier_uniform_


# dataset definition
class CSVDataset(Dataset):
    # load the dataset
    def __init__(self, path):
        # load the csv file as a dataframe
        df = read_csv(path, header=None)
        # store the inputs and outputs
        self.X = df.values[:, :-1]
        self.y = df.values[:, -1]
        # ensure input data is floats
        self.X = self.X.astype('float32')
        # label encode target and ensure the values are floats
        self.y = LabelEncoder().fit_transform(self.y)
        self.y = self.y.astype('float32')
        self.y = self.y.reshape((len(self.y), 1))

    # number of rows in the dataset
    def __len__(self):
```

C:\Users\UB10709\AppData\Roaming\MobaXterm\slash\RemoteFil UNIX Python 187 lines Row #20 Col #1

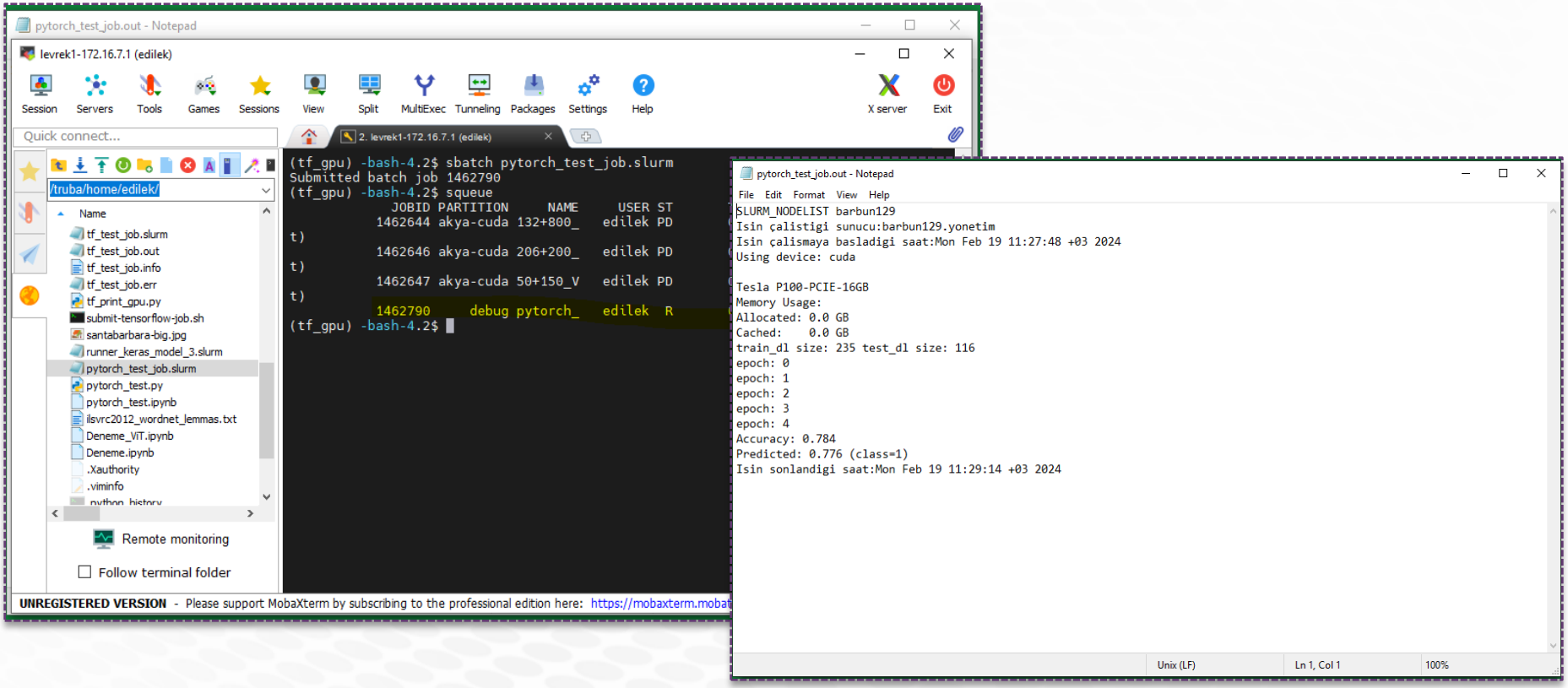
pytorch_test_job.slurm - Notepad

File Edit Format View Help

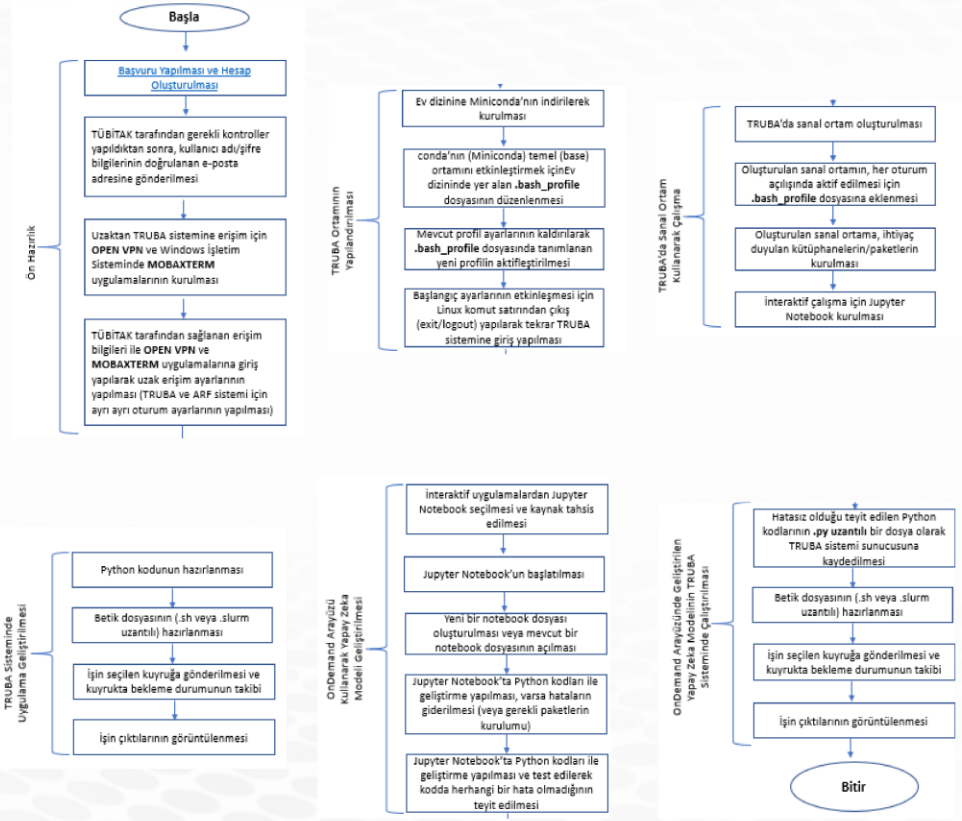
```
#!/bin/bash
#SBATCH -A edilek
#SBATCH -p debug # Debug=15 dk
#SBATCH -C barbun-cuda
#SBATCH -J pytorch_test_job # Gonderilen isin ismi
#SBATCH -o pytorch_test_job.out    # Ciktinin yazilacagi dosya adi
#SBATCH --error=pytorch_test_job.err # Hatanin yazilacagi dosya adi
#SBATCH -N 1 # Gorev kac node'da calisacak?
#SBATCH -n 1 # Ayni gorevden kac adet calistirilacak?
#SBATCH -c 4 # her bir gorev icin kullanilacak cekirdek adedi, varsayilan=1
# is icin talep edilen toplam cekirdek adedi = n x c

#SBATCH --time=00:03:00 #varsayilan sure 2dk

echo "SLURM_NODELIST $SLURM_NODELIST"
echo -n "Isin çalistigi sunucu:"
hostname

echo -n "Isin çalismaya basladigi saat:"
date

python pytorch_test.py

echo -n "Isin sonlandigi saat:"
date

scontrol show job $SLURM_JOB_ID >> pytorch_test_job.info
exit
```

Unix (LF) Ln 13, Col 21 100%

İŞ PAKETİ 1 (1-3 Ay)
Örnek Yapay Zeka Modeli Geliştirilmesi



İŞ PAKETİ 1 (1-3 Ay)
TRUBA Sisteminde AI Modeli Çalıştırılması İş Akışı



İŞ PAKETİ 1 (1-3 Ay)
TRUBA Sistemi Kullanım Kılavuzu Hazırlanması

2024

TRUBA SİSTEMİ KULLANIM KILAVUZU

TRUBA
Türk Ulusal Bilim e-Altyapısı

Hazırlayan: Esma Dilek
Gazi Üniversitesi
5/17/2024

İÇİNDEKİLER

İŞ PAKETİ 2 (1-4 Ay)

Örnek Veri Setlerinin Temini için İzin Süreçlerinin Başlatılması, Verilerin Temini, Test Kamerası Kurulumunun Tamamlanması, TRUBA Platformu Üzerinde Verilerin Erişilebilir Hale Getirilmesi

Örnek veri setleri temini için izin süreçlerinin yürütülmesi

Örnek veri setlerinin ve test kamerasının temin edilerek kurulumunun tamamlanması

TRUBA platfomu üzerinde örnek veri setlerinin erişilebilir hale getirilmesi

İŞ PAKETİ 2 (1-4 Ay)

Örnek Veri Setlerinin Temini için İzin Süreçlerinin Başlatılması, Verilerin Temini, Test Kamerası Kurulumunun Tamamlanması, TRUBA Platformu Üzerinde Verilerin Erişilebilir Hale Getirilmesi

Kaynak: Kuzey Marmara Otoyolu

İstanbul-Kocaeli-Sakarya
Toplam Otoyol Uzunluğu: 443km

KMO ANADOLU
OTOYOL İŞLETMESİ A.Ş.

6 Nisan 2023, Perşembe

ÖZEL İZİN BELGESİ

Sn. Doç. Dr. Murat DENER,
"TÜBİTAK 1005-ULUSAL YENİ FİKİRLER VE ÜRÜNLER ARAŞTIRMA DESTEK PROGRAMI" kapsamında, proje yürütücülüğünüzde başvurusu yapılan, TÜBİTAK Araştırma Destek Programları Başkanlığı tarafından desteklenmesine karar verilen 123E065 numaralı ve "Trafik

KMO ANADOLU
OTOYOL İŞLETMESİ A.Ş.

6 Nisan 2023, Perşembe

PROJE DESTEK MEKTUBU

"TÜBİTAK 1005-ULUSAL YENİ FİKİRLER VE ÜRÜNLER ARAŞTIRMA DESTEK PROGRAMI" kapsamında, Gazi Üniversitesi Fen Bilimleri Enstitüsü Bilgi Güvenliği Mühendisliği Ana Bilim Dalı Başkanı Doç. Dr. Murat DENER proje yürütücülüğünde proje başvurusu yapılan, TÜBİTAK Araştırma Destek Programları Başkanlığı tarafından desteklenmesine karar verilen 123E065 numaralı ve "Trafik Gözlem Kameralarında Derin Öğrenme Yöntemleriyle Gerçek Zamanlı Video Akışı Analizi ve Kötücül Aktivite Tespiti" başlıklı projenin, projenin teknik isterlerine uygun olarak gerçekleştirilebilmesi için KMO ANADOLU OTOYOL İŞLETMESİ A.Ş. olarak gerekli teknik desteğin ve verilerin verileceğini belirtir, çalışmalarınızda başarılar dilerim.

Aynur ULUĞTEKİN
KMO ANADOLU OTOYOL İŞLETMESİ A.Ş.
GENEL MÜDÜRÜ

AVRUPA OTOYOLU
YATIRIM VE İŞLETME A.Ş.

6 Nisan 2023, Perşembe

ÖZEL İZİN BELGESİ

Sn. Doç. Dr
"TÜBİTAK
kapsamında
Programlar
Gözlem Ka
Kötücül Akt
için Kuzey
alan bir kar
sağlanması
yürütmeniz
tamamlanı
sunacağım

AVRUPA OTOYOLU
YATIRIM VE İŞLETME A.Ş.

PROJE DESTEK MEKTUBU

"TÜBİTAK 1005-ULUSAL YENİ FİKİRLER VE ÜRÜNLER ARAŞTIRMA DESTEK PROGRAMI" kapsamında, Gazi Üniversitesi Fen Bilimleri Enstitüsü Bilgi Güvenliği Mühendisliği Ana Bilim Dalı Başkanı Doç. Dr. Murat DENER proje yürütücülüğünde proje başvurusu yapılan, TÜBİTAK Araştırma Destek Programları Başkanlığı tarafından desteklenmesine karar verilen 123E065 numaralı ve "Trafik Gözlem Kameralarında Derin Öğrenme Yöntemleriyle Gerçek Zamanlı Video Akışı Analizi ve Kötücül Aktivite Tespiti" başlıklı projenin, projenin teknik isterlerine uygun olarak gerçekleştirilebilmesi için AVRUPA OTOYOLU YATIRIM VE İŞLETME A.Ş. olarak gerekli teknik desteğin ve verilerin verileceğini belirtir, çalışmalarınızda başarılar dilerim.

Aynur ULUĞTEKİN
AVRUPA OTOYOLU YATIRIM VE İŞLETME A.Ş.
GENEL MÜDÜRÜ

INTRA

Tarih: 5 Nisan 2023, Çarşamba

PROJE DESTEK MEKTUBU

"TÜBİTAK 1005-ULUSAL YENİ FİKİRLER VE ÜRÜNLER ARAŞTIRMA DESTEK PROGRAMI" kapsamında, Gazi Üniversitesi Fen Bilimleri Enstitüsü Bilgi Güvenliği Mühendisliği Ana Bilim Dalı Başkanı Doç. Dr. Murat DENER proje yürütücülüğünde proje başvurusu yapılan, TÜBİTAK Araştırma Destek Programları Başkanlığı tarafından desteklenmesine karar verilen 123E065 numaralı ve "Trafik Gözlem Kameralarında Derin Öğrenme Yöntemleriyle Gerçek Zamanlı Video Akışı Analizi ve Kötücül Aktivite Tespiti" başlıklı projenin, projenin teknik isterlerine uygun olarak gerçekleştirilebilmesi için İNTETRA ELEKTRONİK SANAYİ VE TİCARET A.Ş. olarak gerekli teknik desteğin ve verilerin verileceğini belirtir, çalışmalarınızda başarılar dilerim.

Mehmet ÖMERBEYOĞLU
CEO

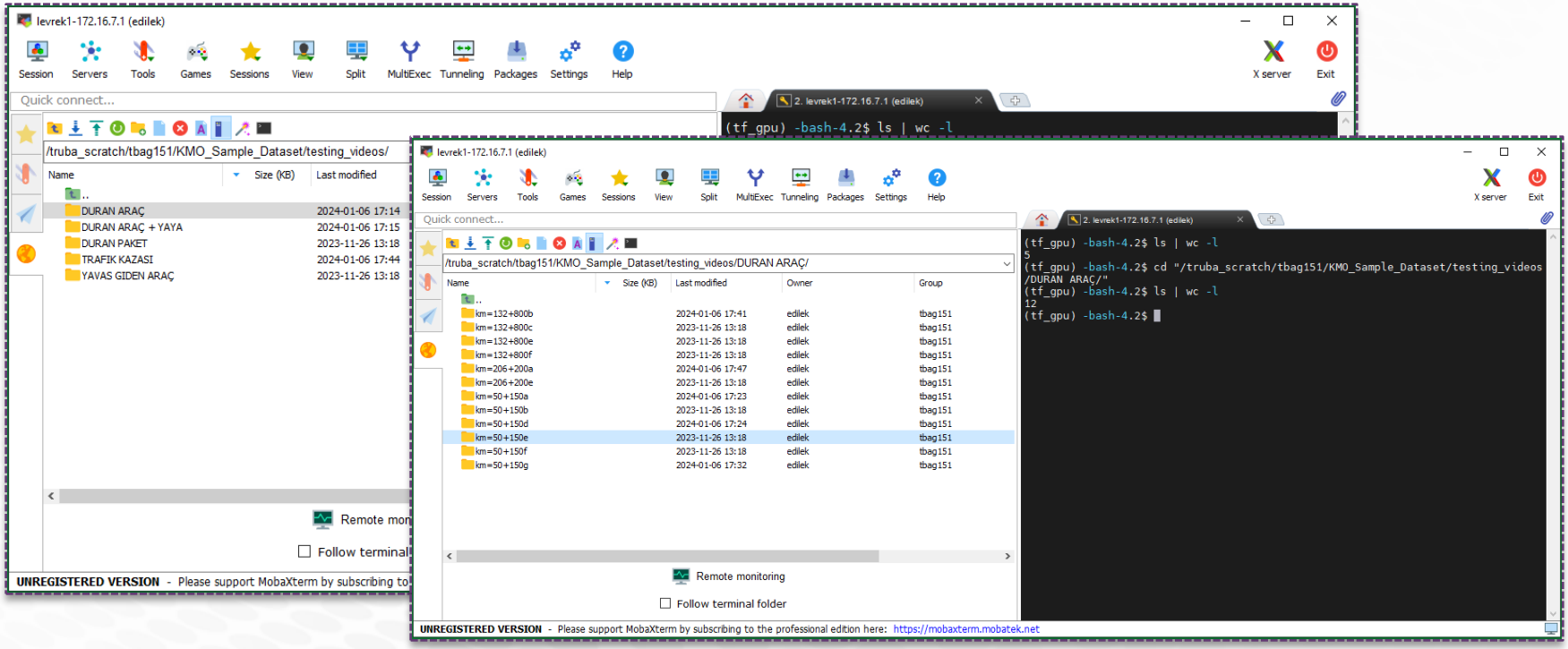
İŞ PAKETİ 2 (1-4 Ay)

Örnek Veri Setlerinin Temini için İzin Süreçlerinin Başlatılması, Verilerin Temini, Test Kamerası Kurulumunun Tamamlanması, TRUBA Platformu Üzerinde Verilerin Erişilebilir Hale Getirilmesi

Kamera Modeli: PELCO P2820L-ESR

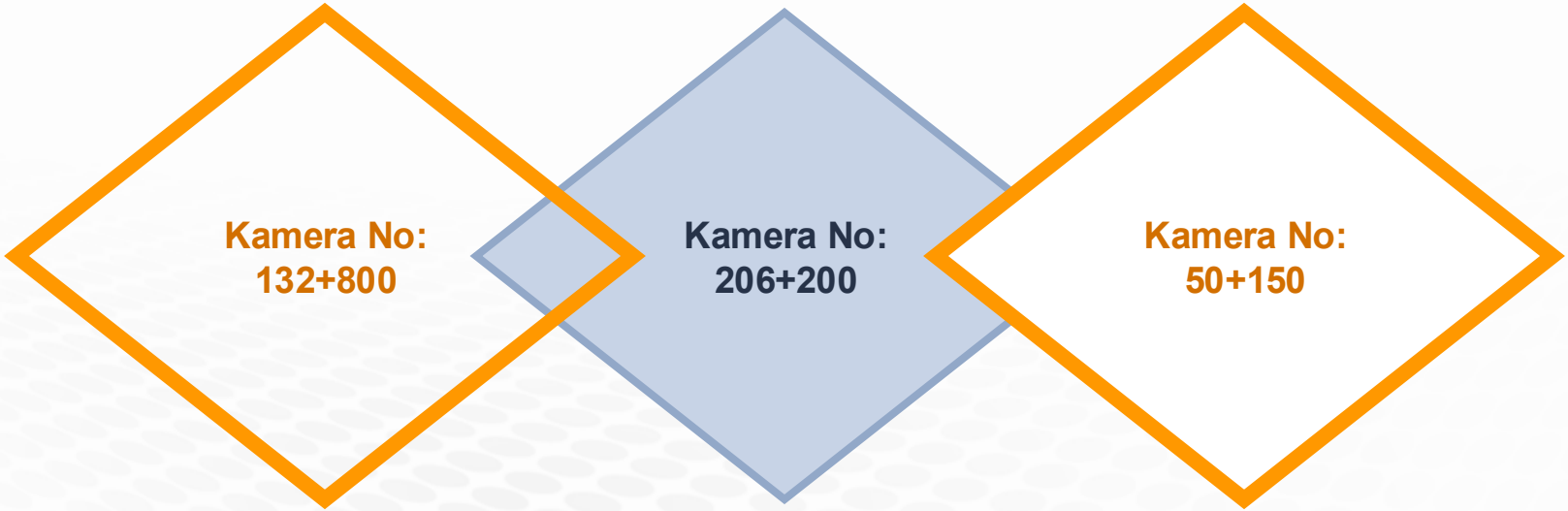
İŞ PAKETİ 2 (1-4 Ay)

Örnek Veri Setlerinin Temini için İzin Süreçlerinin Başlatılması, Verilerin Temini, Test Kamerası Kurulumunun Tamamlanması, TRUBA Platformu Üzerinde Verilerin Erişilebilir Hale Getirilmesi



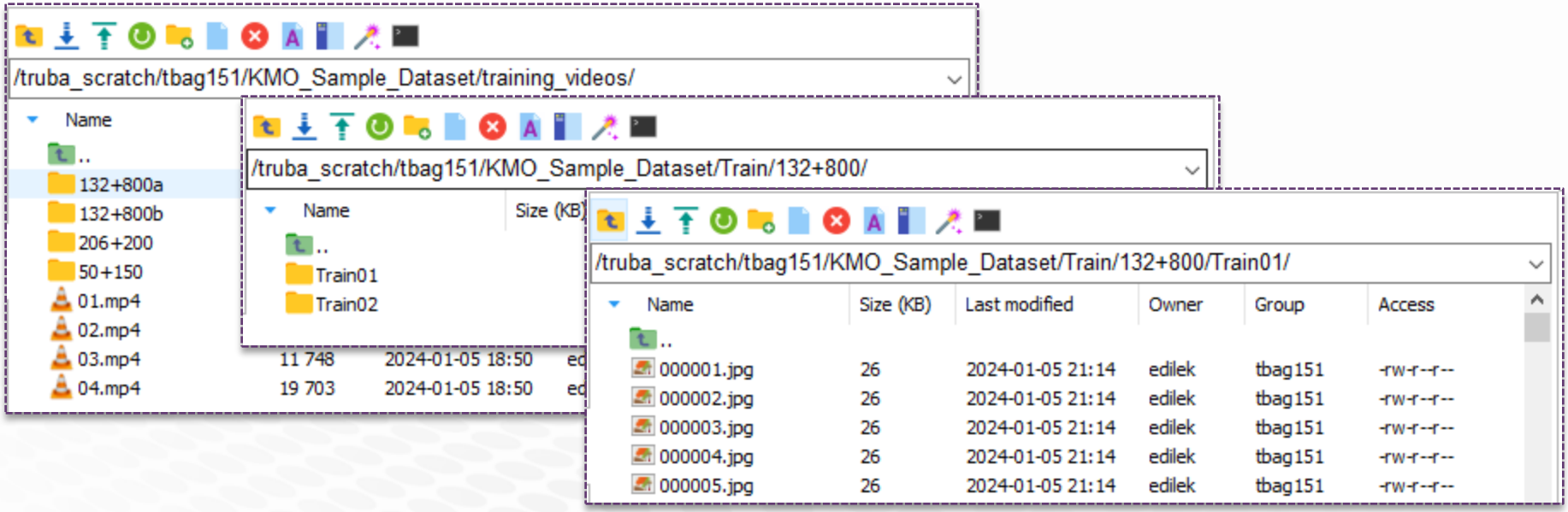
İŞ PAKETİ 3 (4-7 Ay)
Veri Seti Ön İşleme Süreçleri

- Veri seti ön işleme adımlarında yapılan tüm işler için geliştirilen Python kodları "/truba/home/tbag151/VAD/Pre-Process.ipynb" dosyasına kaydedilmiştir.
- Tüm veri seti ön işleme adımları, 3 farklı veri seti için ayrı ayrı uygulanmıştır.



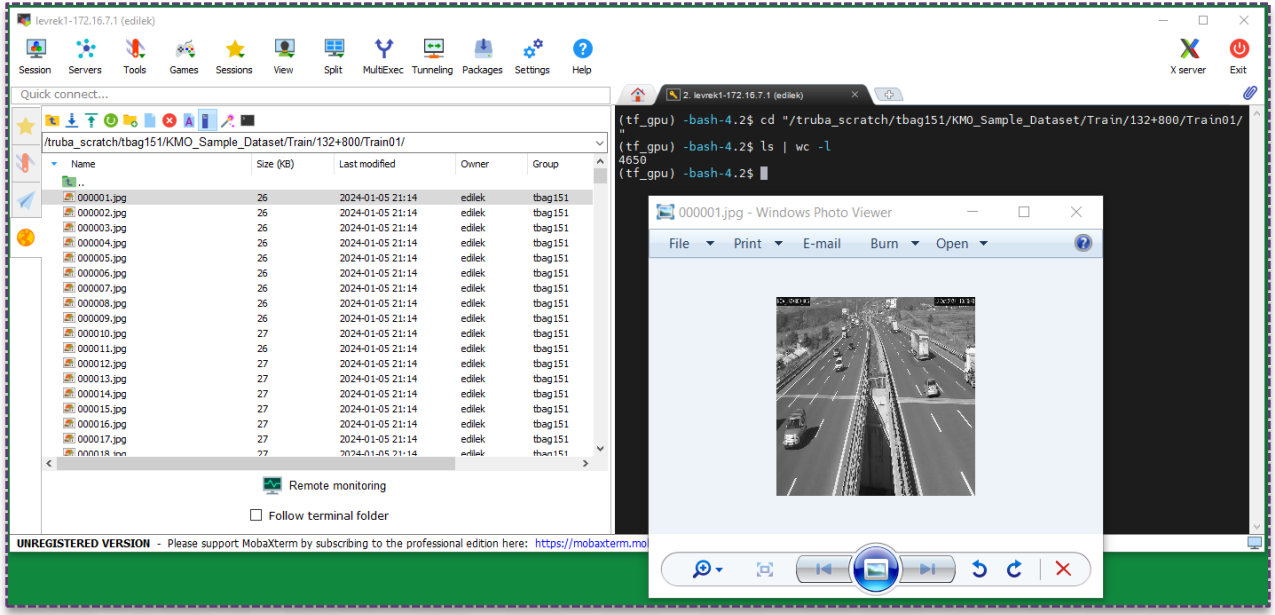
İŞ PAKETİ 3 (4-7 Ay)
Veri Seti Ön İşleme Süreçleri-Eğitim Videolarının İşlenmesi

- İçinde sadece **normal kareler bulunan Eğitim videolarının** (.mp4 formatında) her biri okunarak karelerine ayrılmış ve ayrı ayrı klasörlere kopyalanmıştır **(Train).**
- Her bir kamera no (132+800, 206+200, 50+150) için bu işlem tekrarlanmıştır.



İŞ PAKETİ 3 (4-7 Ay)

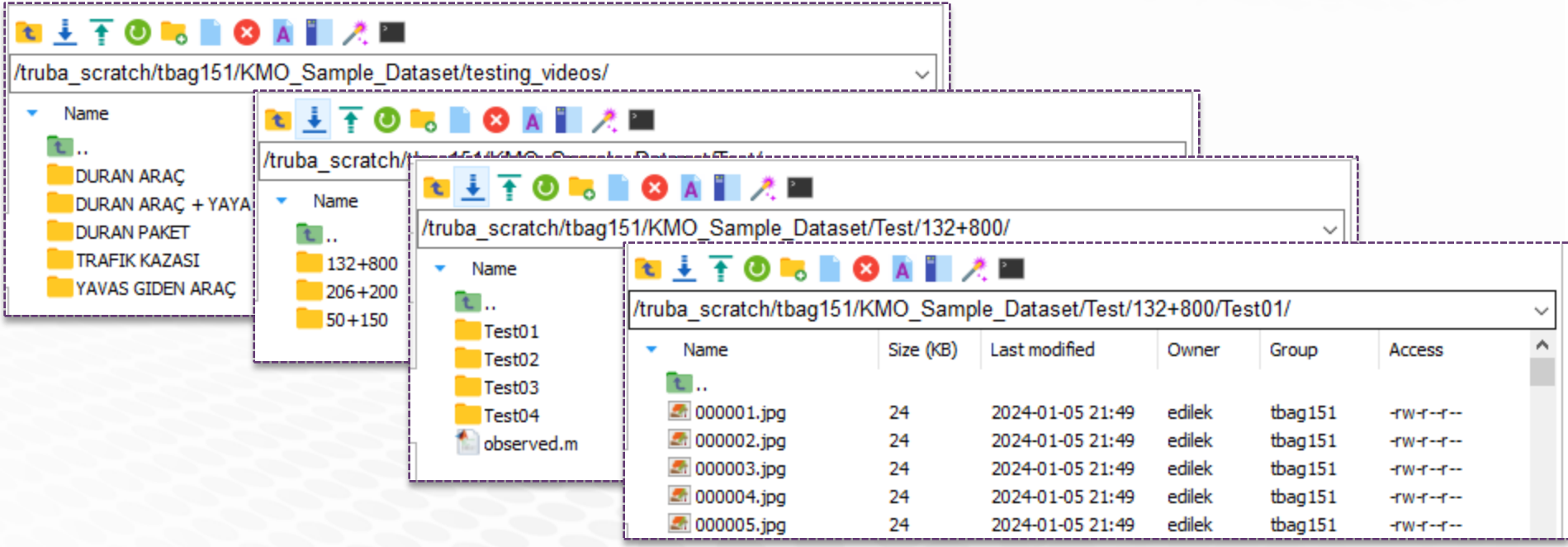
Veri Seti Ön İşleme Süreçleri-Eğitim Videolarının İşlenmesi



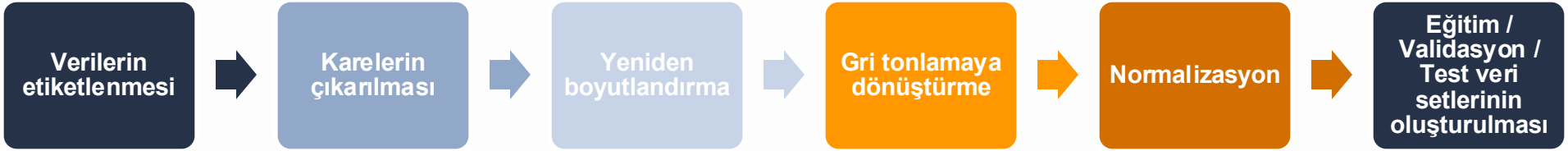
- Eğitim için seçilen videoların karelerinin çıkarılması
- Karelerin 224x224 px olarak yeniden boyutlandırılması
- Karelerin gri tonlamaya dönüştürülmesi ve numaralandırılarak 8-bit .jpg formatında dosya olarak TRUBA ortamına kaydedilmesi

İŞ PAKETİ 3 (4-7 Ay)
Veri Seti Ön İşleme Süreçleri-Test Videolarının İşlenmesi

- İçinde **normal & anomali kareler bulunan Test videolarının** (.mp4 formatında) her biri okunarak karelerine ayrılmış ve ayrı ayrı klasörlere kopyalanmıştır **(Test)**
- Her bir kamera no (132+800, 206+200, 50+150) için bu işlem tekrarlanmıştır.



İŞ PAKETİ 3 (4-7 Ay)
Veri Seti Ön İşleme Süreçleri



İŞ PAKETİ 3 (4-7 Ay)
Veri Seti Ön İşleme Süreçleri

Veri Etiketleme

Eğitim ve **Test videoları**ndaki kareler (Train01, Train02, Test01, Test02, vb. klasörlerde yer alan) **Normal/Anomaly** olarak etiketlenerek etiket bilgileri **observed.m** dosyasına kaydedilmiştir.

Eğitim Veri Seti

Etiketlenmiş tüm kareler, **Training_dataset** klasörü altında **Normal** ve **Anomaly** olarak iki ana sınıfa ayrılmıştır.

Validasyon Veri Seti

Training_dataset klasörü altında bulunan **Normal** ve **Anomaly** klasörlerindeki karelerden **rasgele %20**'si seçilerek **Validation_dataset** oluşturulmuştur.

Test Veri Seti

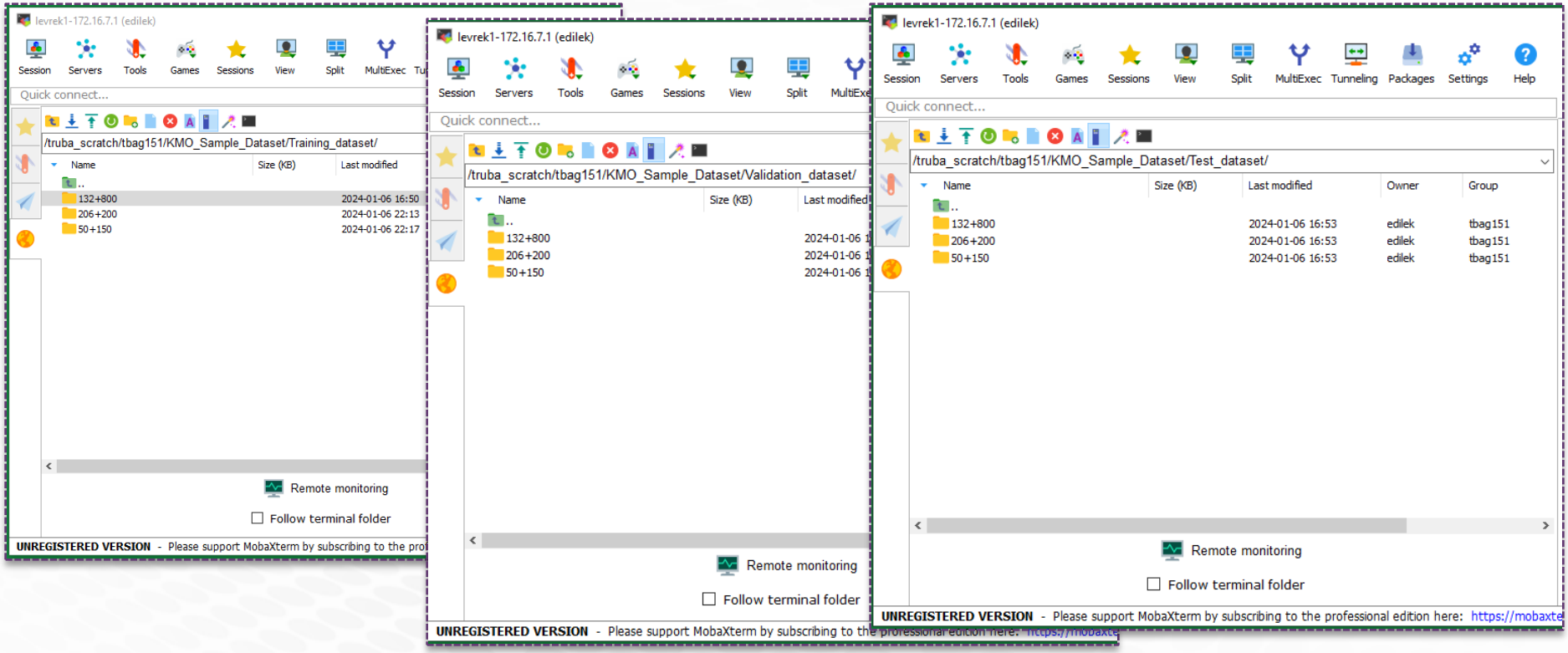
Validation_dataset klasörü altında bulunan **Normal** ve **Anomaly** klasörlerindeki karelerden **rasgele %20**'si seçilerek **Test_dataset** oluşturulmuştur.

İŞ PAKETİ 3 (4-7 Ay)
Veri Seti Ön İşleme Süreçleri - Eğitim/Validasyon/Test Veri Setlerinin Oluşturulması

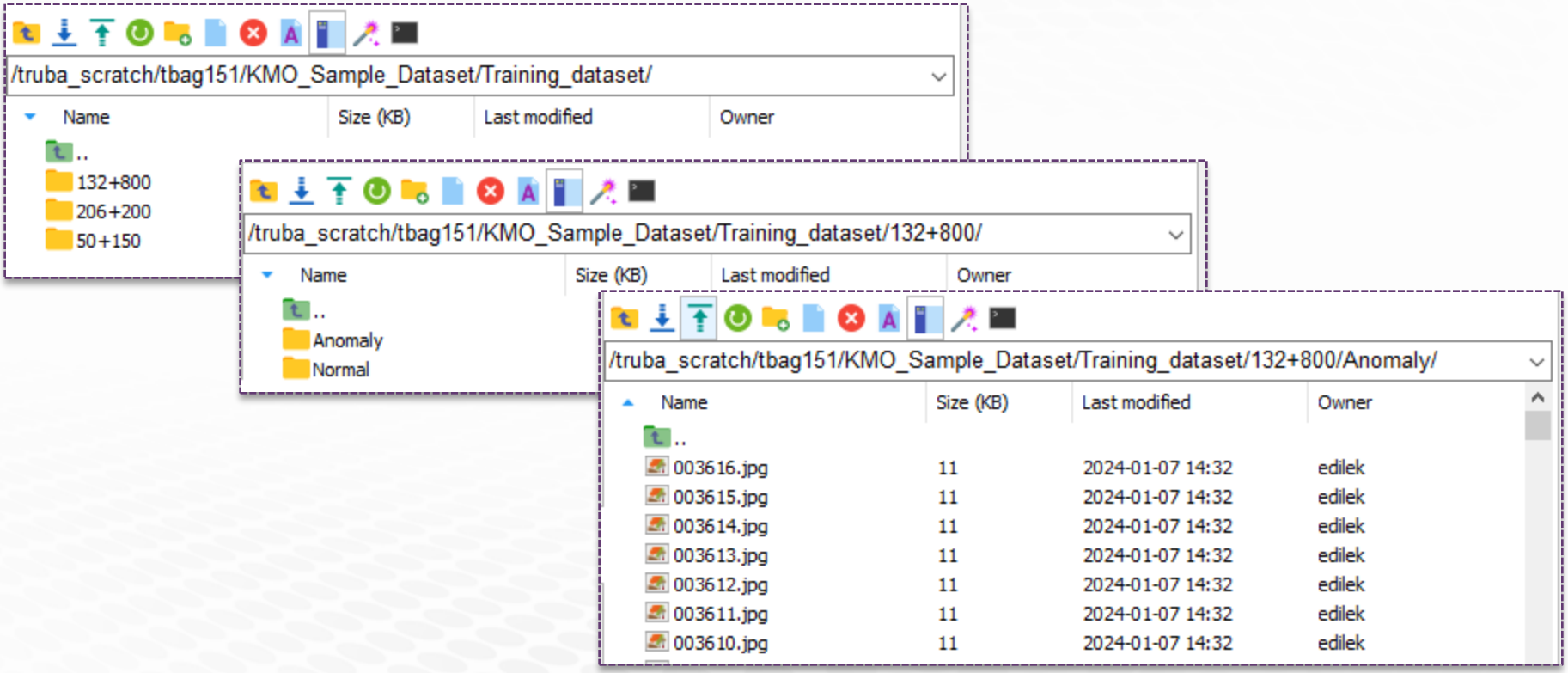
Veri Seti Adı (Kamera No)	Veri Etiketi	Eğitim	Validasyon	Test	Toplam
50+150	Normal	5.060	1.012	254	6.326
	Anomali	10.944	2.189	548	13.681
	Toplam	16.004	3.201	802	20.007
206+200	Normal	7.705	1.352	339	8.452
	Anomali	9.914	1.791	448	11.195
	Toplam	17.619	3.143	787	21.549
132+800	Normal	9.841	19.68	493	12.302
	Anomali	2.892	579	145	3.616
	Toplam	12.733	2.547	638	15.918

İŞ PAKETİ 3 (4-7 Ay)

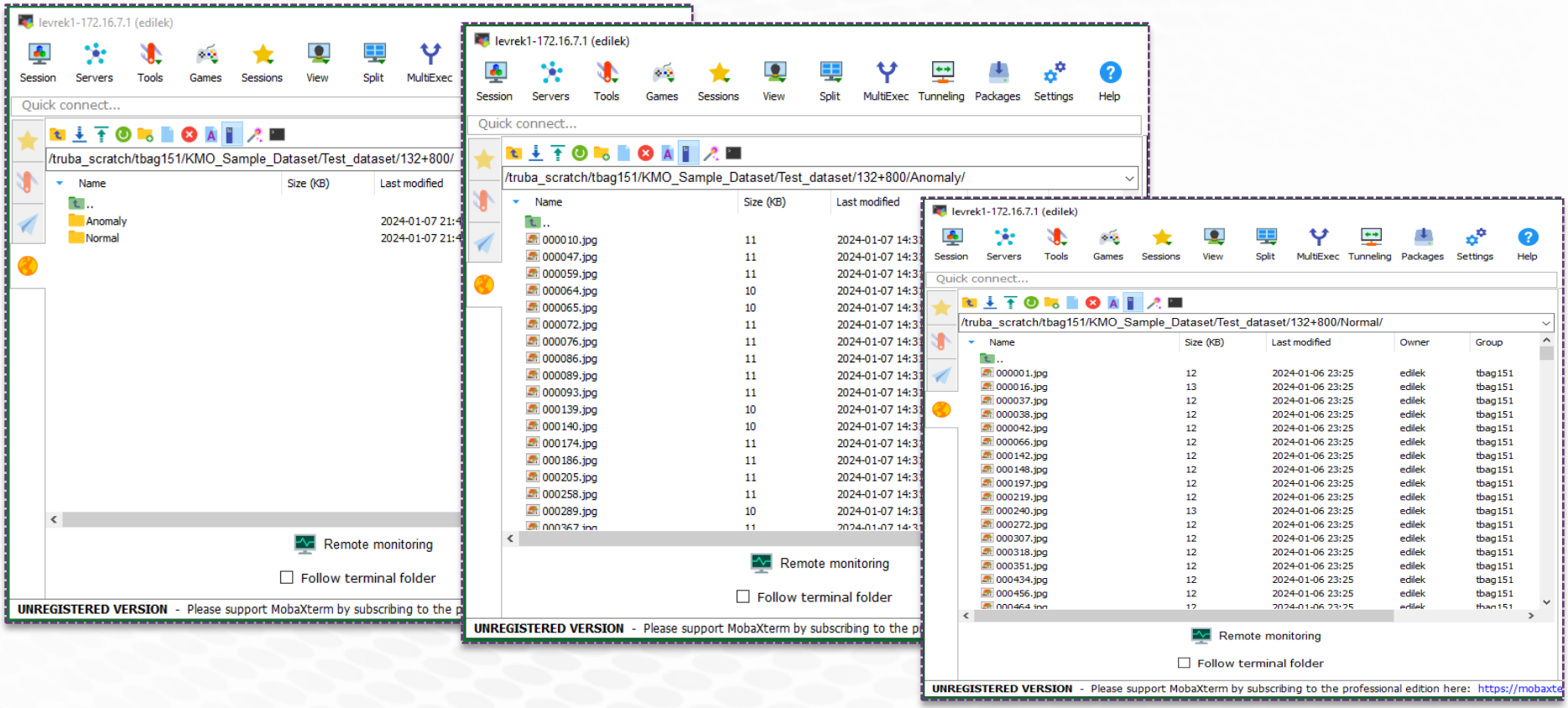
Veri Seti Ön İşleme Süreçleri-Eğitim/Validasyon/Test Veri Setlerinin Oluşturulması



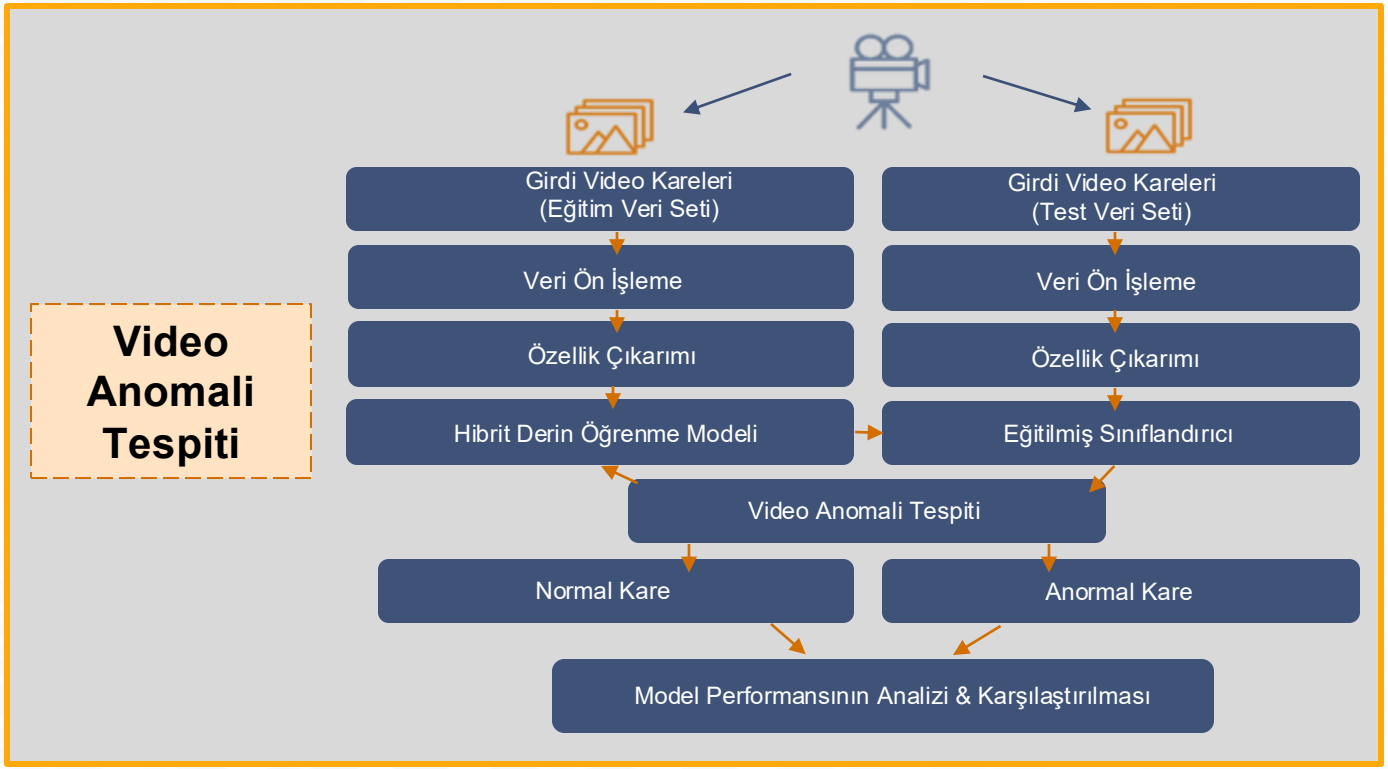
İŞ PAKETİ 3 (4-7 Ay)
Veri Seti Ön İşleme Süreçleri-Eğitim Veri Seti



İŞ PAKETİ 3 (4-7 Ay)
Veri Seti Ön İşleme Süreçleri-Test Veri Seti



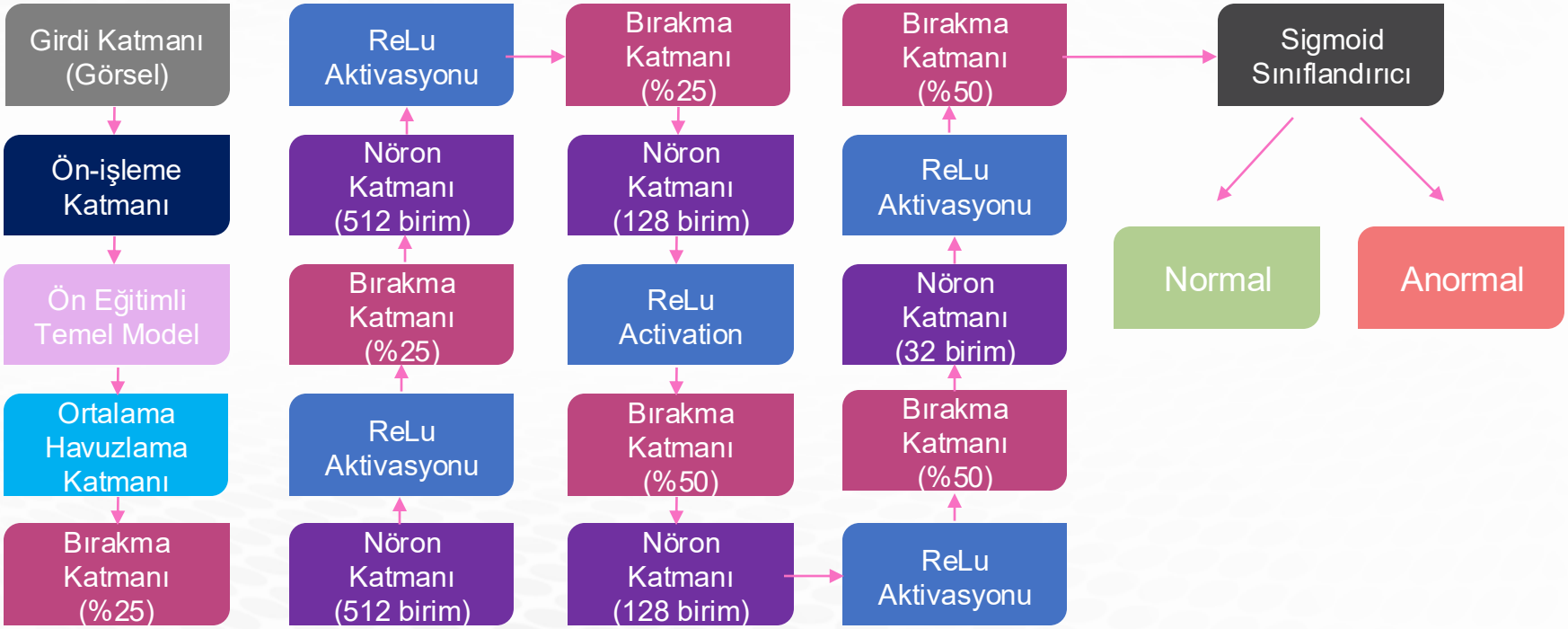
İŞ PAKETİ 4 (7-15 Ay)
Hibrit Derin Öğrenme Modelleri Geliştirilmesi



İŞ PAKETİ 4 (7-15 Ay)

Hibrit Derin Öğrenme Modelleri Geliştirilmesi

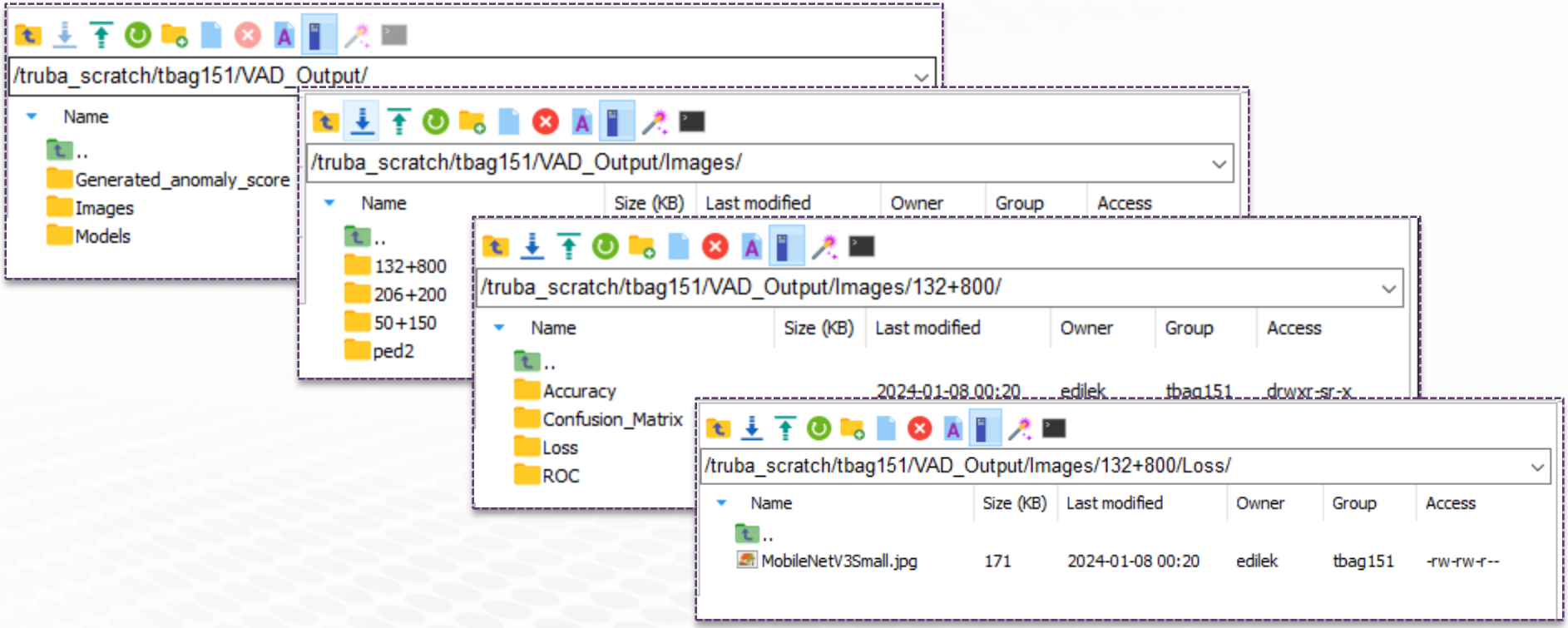
Transfer Learning-Fine Tuning Based Video Anomaly Detection (TL-FT Based VAD)



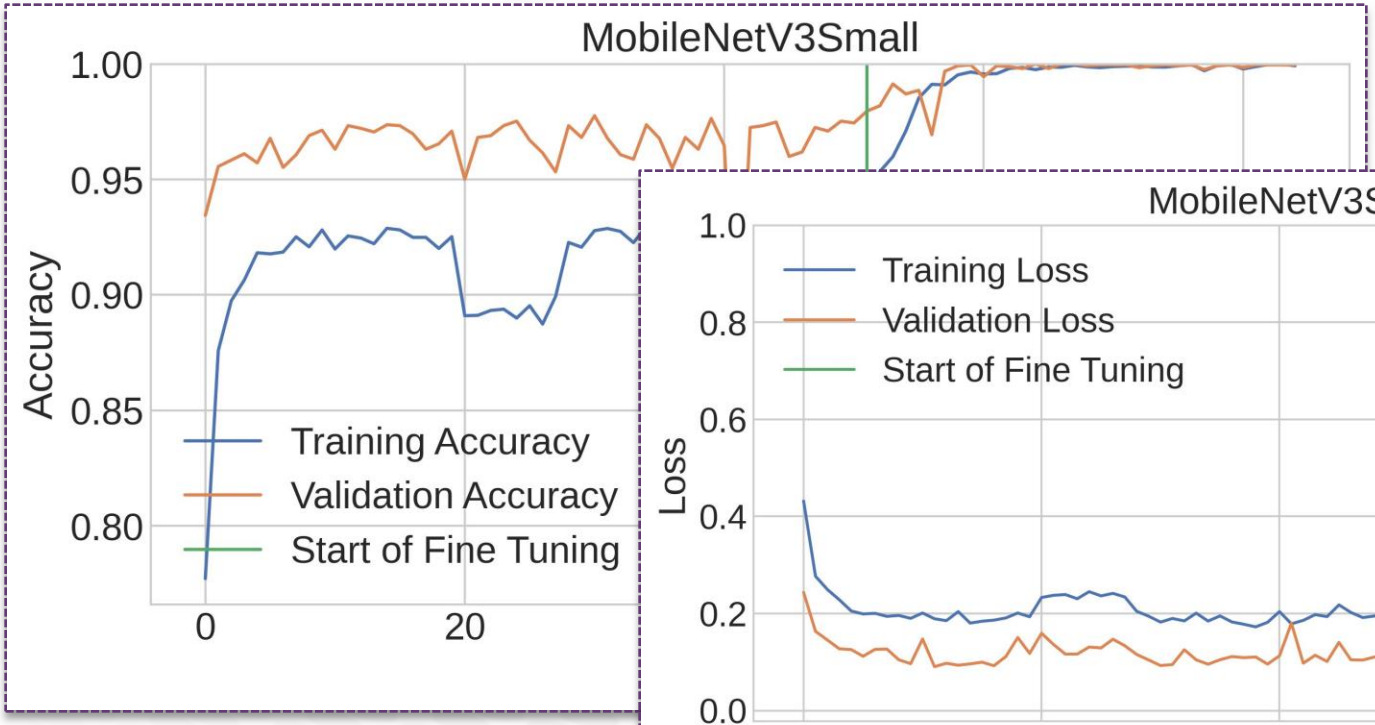
İŞ PAKETİ 4 (7-15 Ay)
Hibrit Derin Öğrenme Modelleri Geliştirilmesi
TL-FT Based VAD / Temel Modeller (Keras Uygulamaları)

VGG16	VGG19	Xception	MobileNetV3Small	MobileNetV3Large
InceptionV3	EfficientNetB0	EfficientNetB1	EfficientNetB2	EfficientNetB3
EfficientNetB4	EfficientNetB5	EfficientNetB6	EfficientNetB7	EfficientNetV2B0
ResNet101V2	DenseNet121	NASNetMobile	NASNetLarge	ConvNeXtTiny

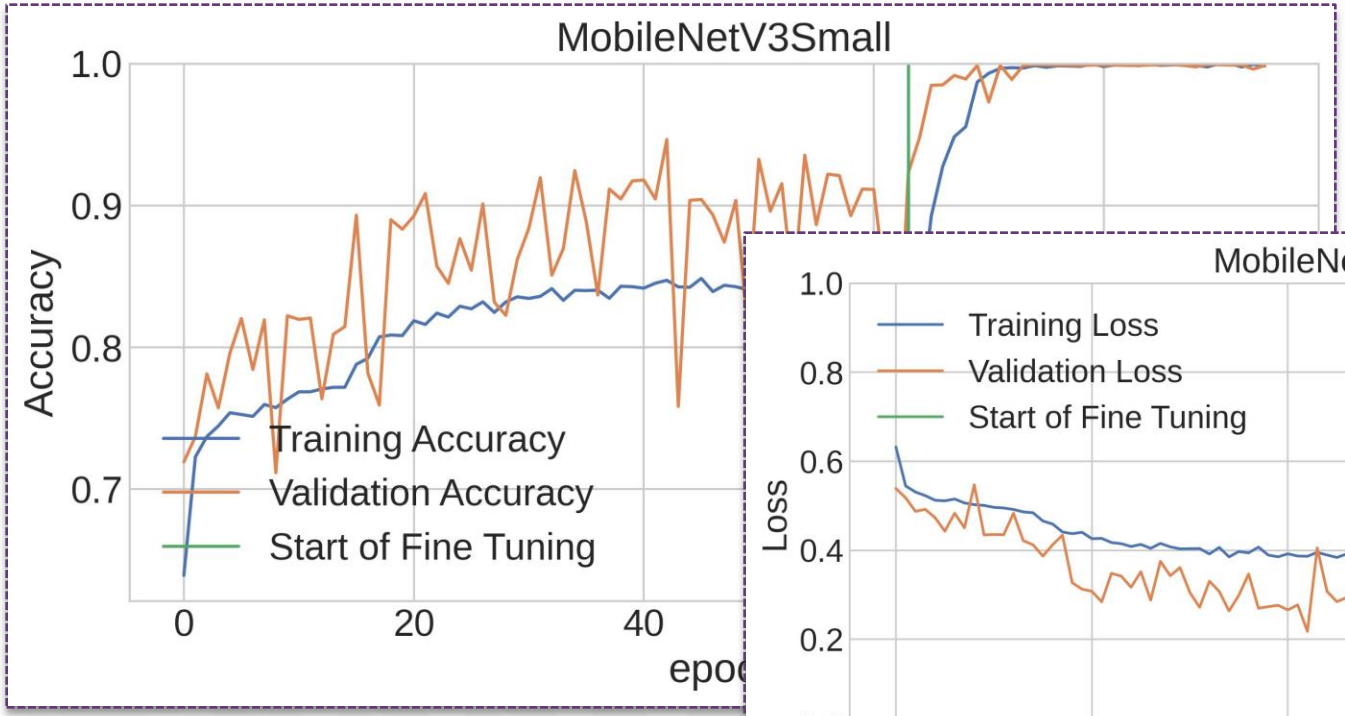
İŞ PAKETİ 4 (7-15 Ay)
Hibrit Derin Öğrenme Modelleri Geliştirilmesi
TL-FT Based VAD - Kamera No:132+800

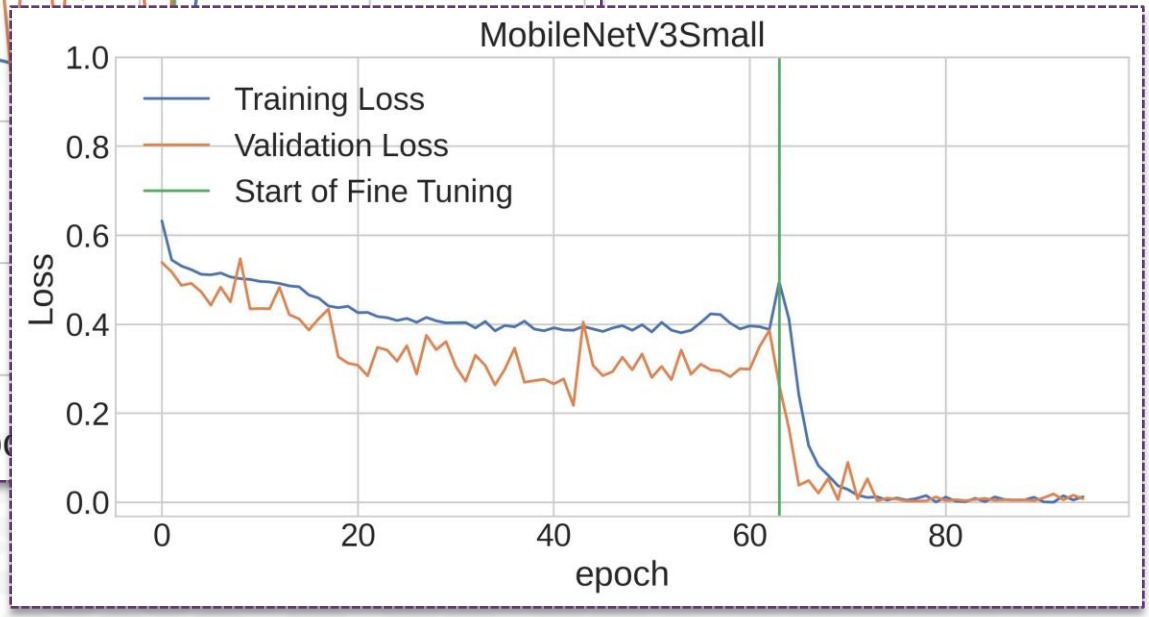


İŞ PAKETİ 4 (7-15 Ay)
Hibrit Derin Öğrenme Modelleri Geliştirilmesi
TL-FT Based VAD - Kamera No:132+800

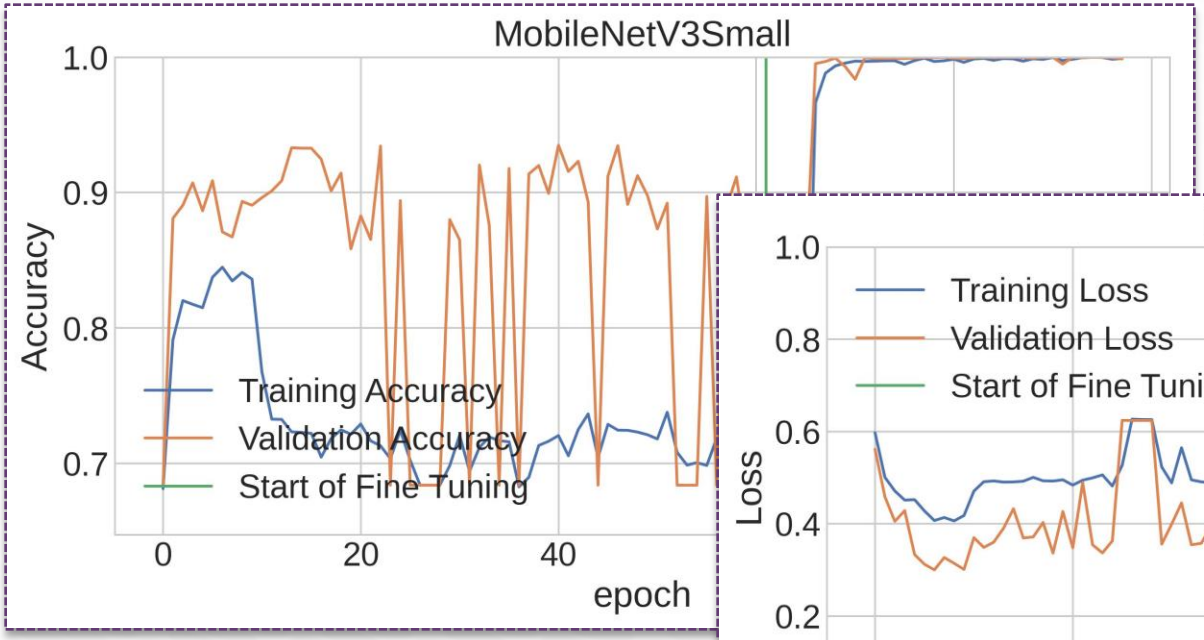


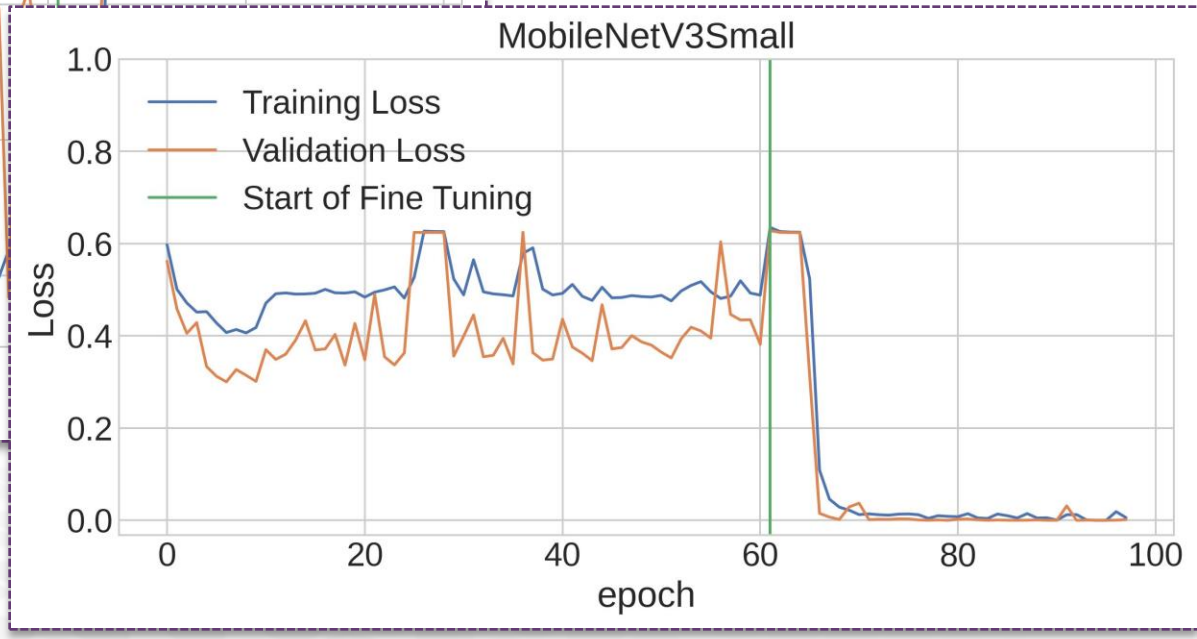
İŞ PAKETİ 4 (7-15 Ay)
Hibrit Derin Öğrenme Modelleri Geliştirilmesi
TL-FT Based VAD - Kamera No:206+200



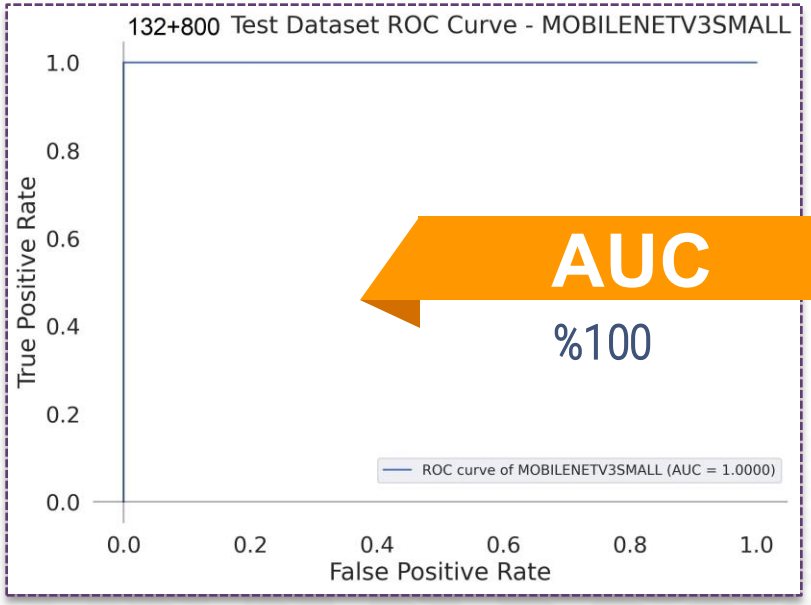


İŞ PAKETİ 4 (7-15 Ay)
Hibrit Derin Öğrenme Modelleri Geliştirilmesi
TL-FT Based VAD - Kamera No:50+150



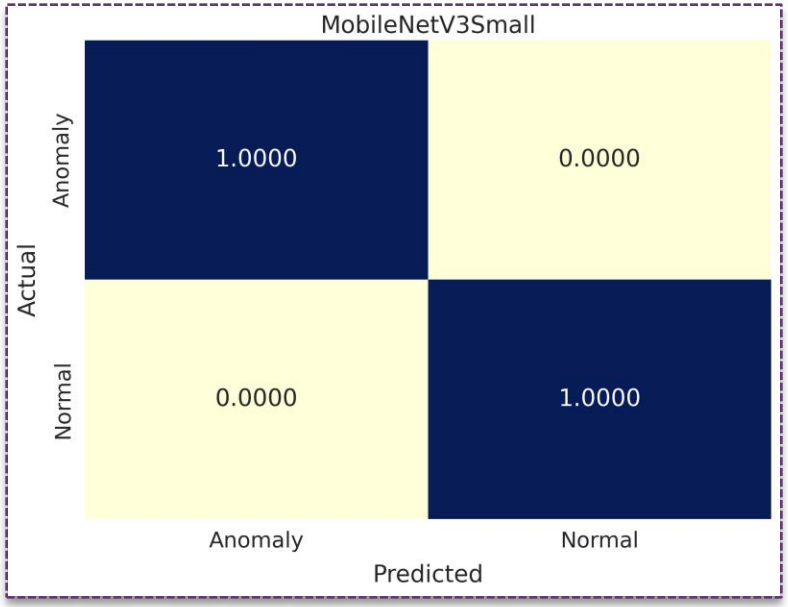


İŞ PAKETİ 5 (7-15 Ay)
Modellerin Test Edilmesi ve Sonuçların Değerlendirilmesi
TL-FT Based VAD - Kamera No:132+800

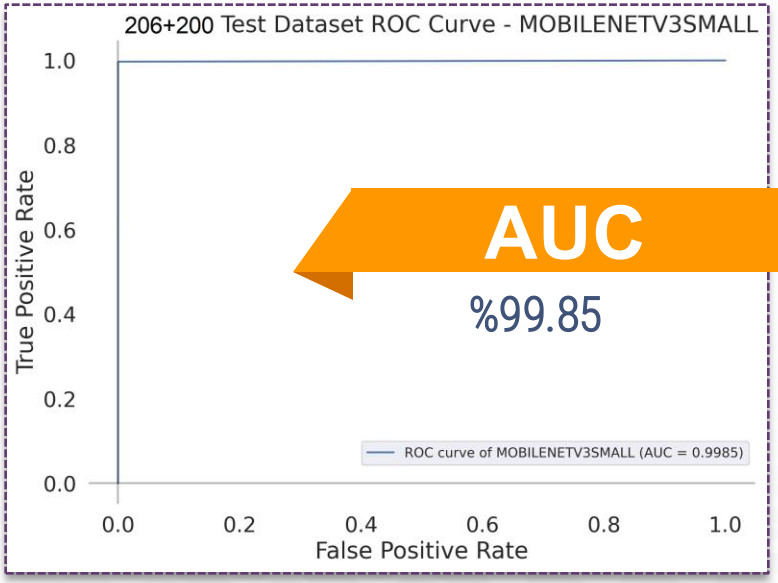


AUC

%100

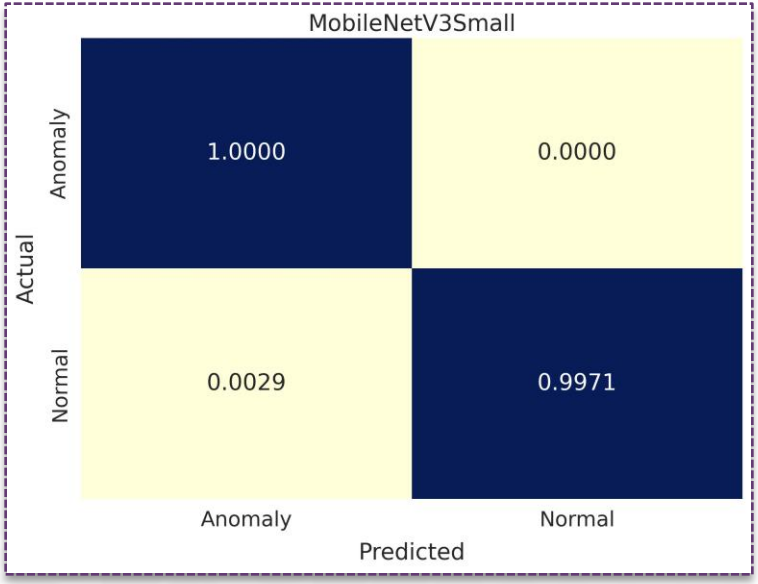


İŞ PAKETİ 5 (7-15 Ay)
Modellerin Test Edilmesi ve Sonuçların Değerlendirilmesi
TL-FT Based VAD - Kamera No:206+200

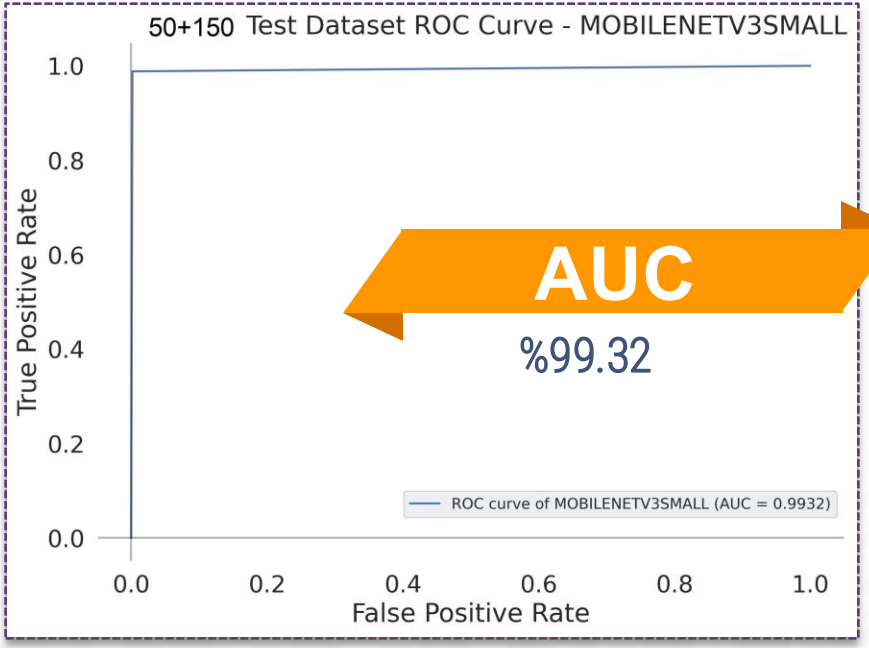


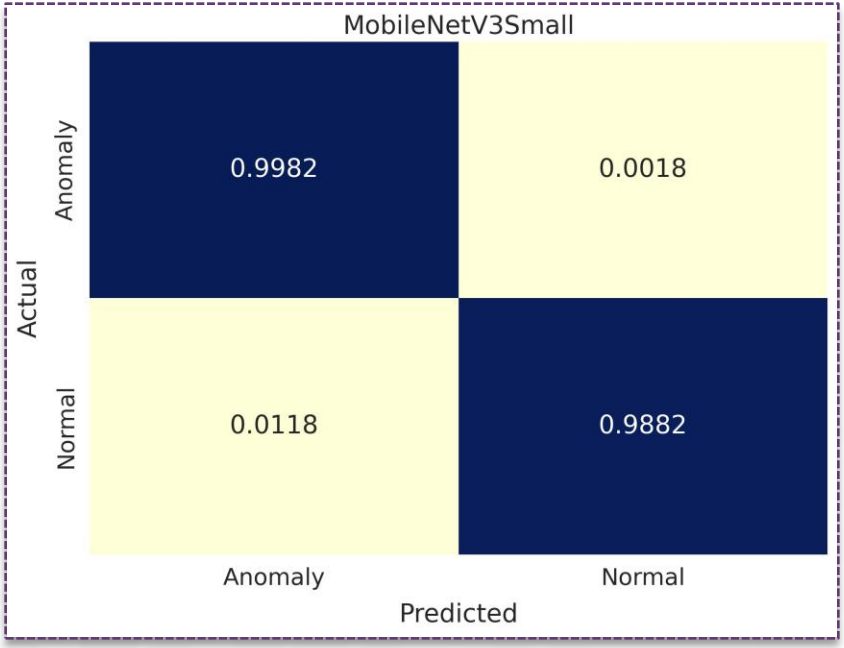
AUC

%99.85



İŞ PAKETİ 5 (7-15 Ay)
Modellerin Test Edilmesi ve Sonuçların Değerlendirilmesi
TL-FT Based VAD - Kamera No:50+150



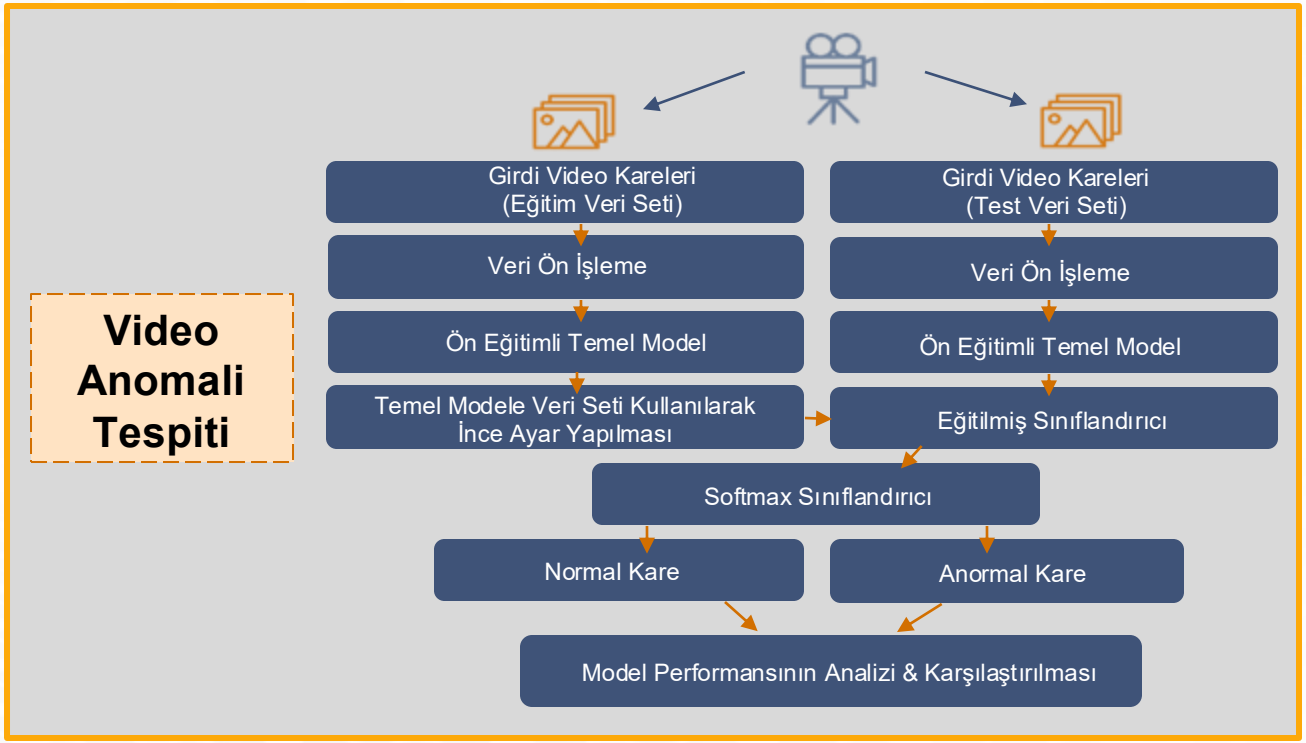


İŞ PAKETİ 5 (7-15 Ay)
Modellerin Test Edilmesi ve Sonuçların Değerlendirilmesi
TL-FT Based VAD – Kamera No:132+800

İŞ PAKETİ 5 (7-15 Ay)
Modellerin Test Edilmesi ve Sonuçların Değerlendirilmesi
TL-FT Based VAD – Kamera No:132+800

İŞ PAKETİ 5 (7-15 Ay)
Modellerin Test Edilmesi ve Sonuçların Değerlendirilmesi
TL-FT Based VAD – PELCO Test Kamerası

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained Vision Transformers



İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained Vision Transformers

ConvNeXT

EfficientFormer

FasterViT

LeViT

MobileViT

SegFormer

SwinTransformer

SwinTransformerV2

VisionTransformer (ViT)

ViTHybrid

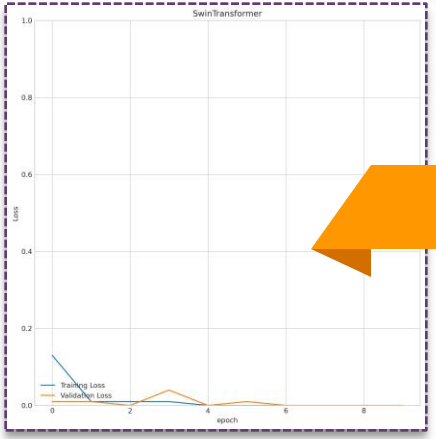
İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained Vision Transformers (50+150)

Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
ConvNeXT	0,0006	0,9997	0,0096	0,9975	0,9982	0,9982	0,9982	**0,9971**	0,0329	0,0228	<0,0000	527	73	<0,0000
EfficientFormer	0,0003	1,0000	0,0099	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,0183	0,0131	<0,0000	293	42	<0,0000
FasterViT	0,0042	0,9988	0,0279	0,9963	0,9964	0,9982	0,9973	**0,9952**	0,0236	0,0184	<0,0000	377	59	<0,0000
LeViT	0,0029	1,0000	0,0126	0,9975	0,9982	0,9982	0,9982	**0,9971**	0,0207	0,0200	<0,0000	332	64	<0,0000
MobileViT	0,0022	0,9997	0,0128	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,0288	0,0266	<0,0000	461	85	<0,0000
SegFormer	0,0005	0,9997	0,0118	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,0735	0,0525	<0,0000	1.176	168	<0,0000
SwinTransformer	0,0002	1,0000	0,0169	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,0305	0,0219	<0,0000	488	70	<0,0000
SwinTransformerV2	0,0006	1,0000	0,0122	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,0647	0,0369	<0,0000	1.035	118	<0,0000
VisionTransformer	0,0027	0,9988	0,0261	0,9950	0,9945	0,9982	0,9964	**0,9932**	0,0649	0,0353	<0,0000	1.039	113	<0,0000
ViTHybrid	0,0000	1,0000	0,0083	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,2320	0,1250	<0,0000	3.713	400	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained SwinTransformer (50+150)

Doğruluk

%99.88

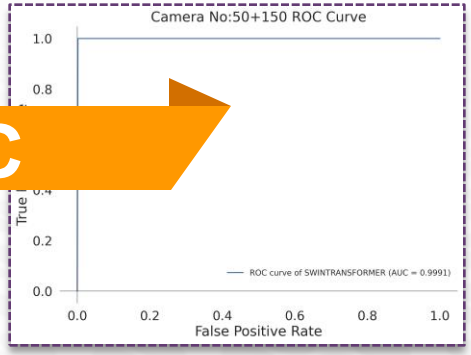


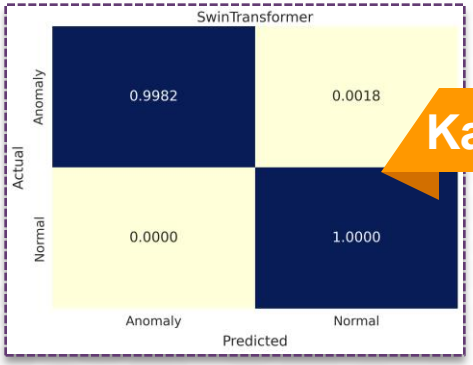
Kayıp

%1.69

AUC

%99.91





Karmaşıklık Matrisi

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained Vision Transformers (206+200)

Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
ConvNeXT	0,0001	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0301	0,0226	<0,0000	530	71	<0,0000
EfficientFormer	0,0001	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0348	0,0350	<0,0000	614	110	<0,0000
FasterViT	0,0021	0,9994	0,0002	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0295	0,0235	<0,0000	520	74	<0,0000
LeViT	0,0018	0,9997	0,0012	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0396	0,0496	<0,0000	697	156	<0,0000
MobileViT	0,0097	0,9972	0,0090	0,9975	1,0000	0,9955	0,9978	**0,9978**	0,0379	0,0369	<0,0000	668	116	<0,0000
SegFormer	0,0002	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0747	0,0897	<0,0000	1.317	282	<0,0000
SwinTransformer	0,0017	0,9994	0,0016	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0469	0,0455	<0,0000	826	143	<0,0000
SwinTransformerV2	0,0003	0,9997	0,0002	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0639	0,0668	<0,0000	1.126	210	<0,0000
VisionTransformer	0,0033	0,9991	0,0008	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0657	0,0363	<0,0000	1.158	114	<0,0000
ViTHybrid	0,0046	0,9984	0,0112	0,9936	0,9911	0,9978	0,9944	**0,9930**	0,2555	0,1696	<0,0000	4.501	533	<0,0000

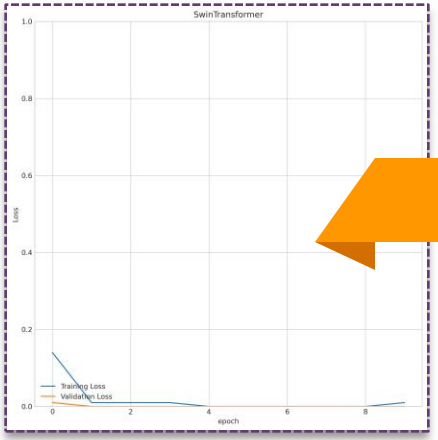
İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained SwinTransformer (206+200)

Doğruluk

%100

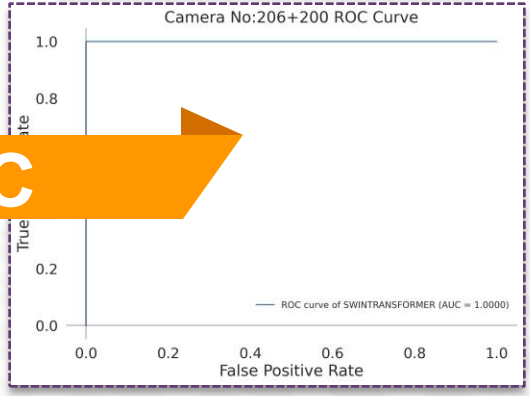
Kayıp

%0.16

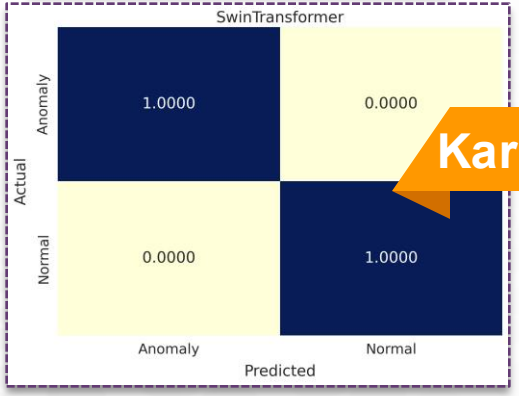


AUC

%100



Karmaşıklık Matrisi



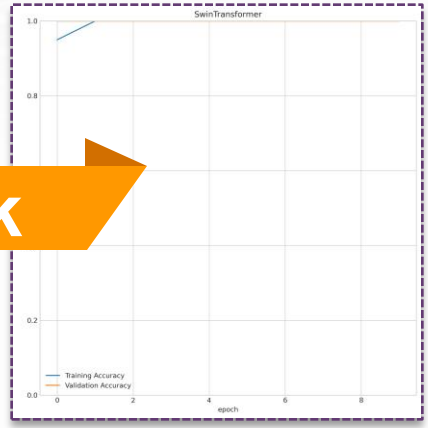
İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained Vision Transformers (132+800)

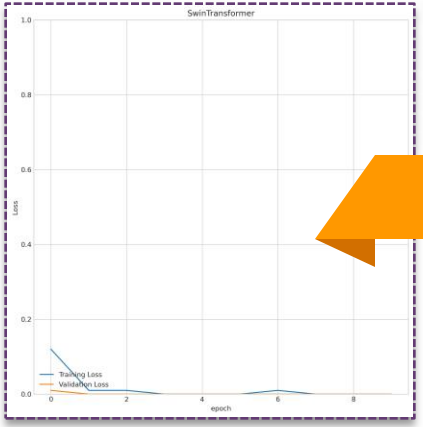
Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
ConvNeXT	0,0004	1,0000	0,0014	0,9984	0,9932	1,0000	0,9966	**0,9990**	0,0432	0,0526	<0,0000	550	134	<0,0000
EfficientFormer	0,0011	0,9996	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0360	0,0330	<0,0000	459	84	<0,0000
FasterViT	0,0025	0,9996	0,0046	0,9969	0,9864	1,0000	0,9932	**0,9980**	0,0197	0,0157	<0,0000	251	40	<0,0000
LeViT	0,0340	0,9969	0,0222	0,9953	1,0000	0,9793	0,9895	**0,9897**	0,0158	0,0145	<0,0000	201	37	<0,0000
MobileViT	0,0097	0,9984	0,0026	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0300	0,0271	<0,0000	382	69	<0,0000
SegFormer	0,0007	0,9996	0,0001	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0659	0,0432	<0,0000	839	110	<0,0000
SwinTransformer	0,0000	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0496	0,0440	<0,0000	631	112	<0,0000
SwinTransformerV2	0,0003	1,0000	0,0001	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0433	0,0346	<0,0000	551	88	<0,0000
VisionTransformer	0,0016	0,9996	0,0001	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0320	0,0220	<0,0000	408	56	<0,0000
ViTHybrid	0,0028	0,9996	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,2413	0,1170	<0,0000	3.072	298	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained SwinTransformer (132+800)

Doğruluk

%100



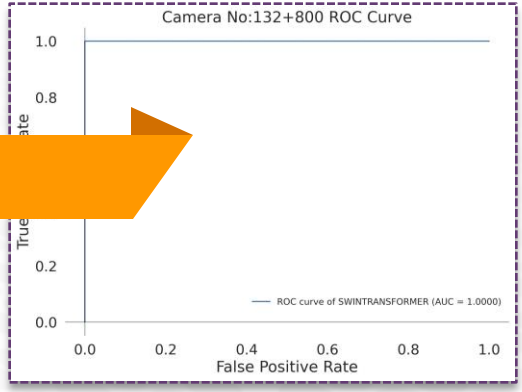


Kayıp

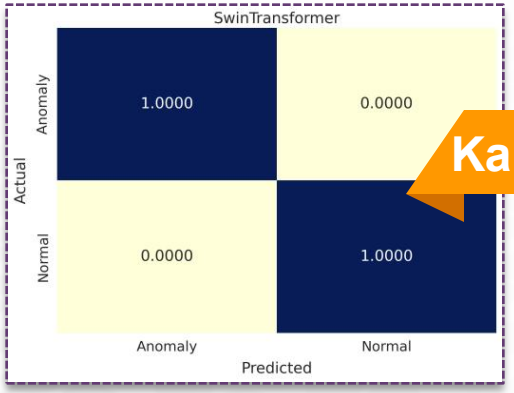
%0.00

AUC

%100



Karmaşıklık Matrisi



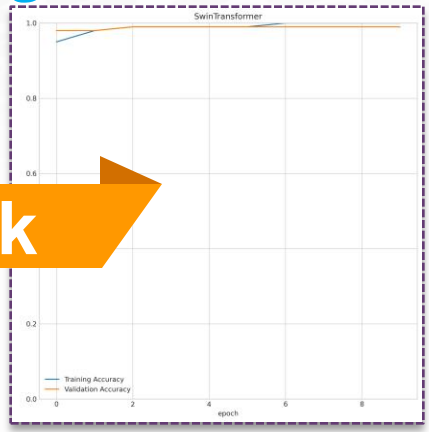
İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained Vision Transformers (CUHK Avenue)

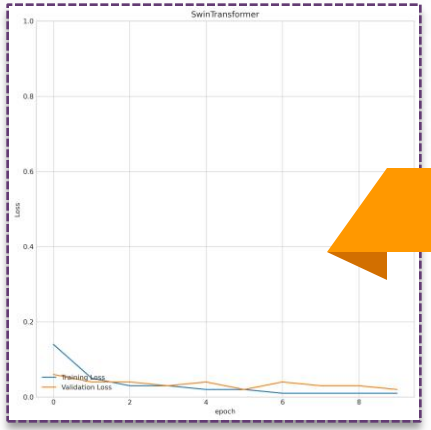
Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
ConvNeXT	0,0189	0,9958	0,0309	0,9943	0,9662	0,9862	0,9761	**0,9908**	0,0431	0,0500	<0,0000	1.058	245	<0,0000
EfficientFormer	0,0278	0,9930	0,0605	0,9886	0,9517	0,9517	0,9517	**0,9726**	0,0199	0,0184	<0,0000	489	90	<0,0000
FasterViT	0,0682	0,9736	0,0817	0,9707	0,8303	0,9448	0,8839	**0,9595**	0,0750	0,0673	<0,0000	1.838	330	<0,0000
LeViT	0,1806	0,9536	0,1462	0,9438	0,7436	0,8000	0,7708	**0,8815**	0,0392	0,0410	<0,0000	960	201	<0,0000
MobileViT	0,0256	0,9914	0,0284	0,9910	0,9589	0,9655	0,9622	**0,9800**	0,0277	0,0324	<0,0000	680	159	<0,0000
SegFormer	0,0426	0,9885	0,0449	0,9829	0,9026	0,9586	0,9298	**0,9724**	0,0640	0,0663	0,0008	1.570	325	1,0000
SwinTransformer	0,0179	0,9946	0,0301	0,9910	0,9718	0,9517	0,9617	**0,9740**	0,0358	0,0398	<0,0000	877	195	<0,0000
SwinTransformerV2	0,0369	0,9902	0,0582	0,9813	0,8812	0,9724	0,9246	**0,9774**	0,0539	0,0508	<0,0000	1.321	249	<0,0000
VisionTransformer	0,0222	0,9934	0,0538	0,9870	0,9388	0,9517	0,9452	**0,9717**	0,0645	0,0394	<0,0000	1.581	193	<0,0000
ViTHybrid	0,0250	0,9938	0,0371	0,9894	0,9714	0,9379	0,9544	**0,9671**	0,2292	0,1307	<0,0000	5.619	641	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained SwinTransformer (CUHK Avenue)

Doğruluk

%99.10



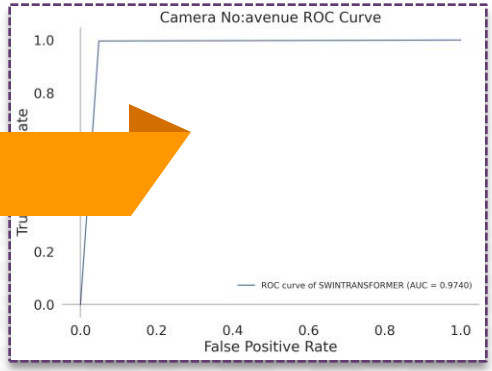


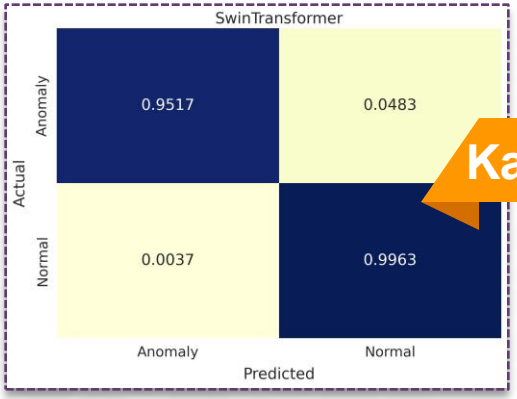
Kayıp

%3.01

AUC

%97.40





Karmaşıklık Matrisi

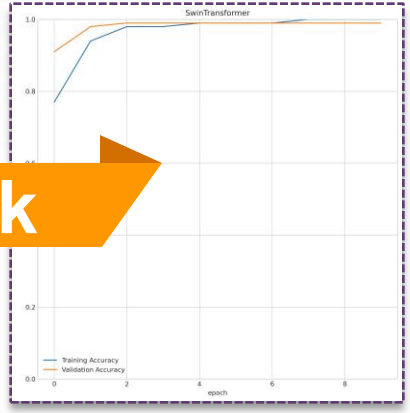
İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained Vision Transformers (UCSD Ped1)

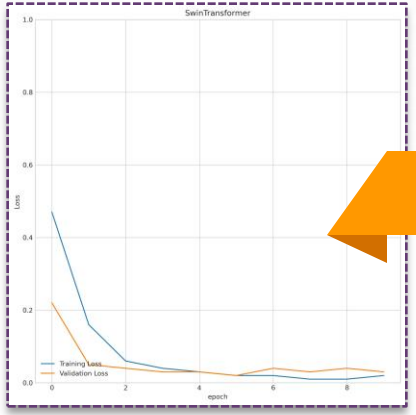
Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
ConvNeXT	0,0138	0,9952	0,0159	0,9964	1,0000	0,9877	0,9938	**0,9938**	0,0305	0,0228	<0,0000	342	51	<0,0000
EfficientFormer	0,0323	0,9913	0,0129	0,9947	0,9877	0,9938	0,9908	**0,9944**	0,0139	0,0134	<0,0000	156	30	<0,0000
FasterViT	0,2043	0,9214	0,2407	0,9073	0,9583	0,7099	0,8156	**0,8487**	0,0640	0,0598	<0,0000	717	134	<0,0000
LeViT	1,7662	0,8306	0,4006	0,7273	0,5159	0,9012	0,6562	**0,7789**	0,0225	0,0152	<0,0000	252	34	<0,0000
MobileViT	0,0330	0,9922	0,0314	0,9875	0,9697	0,9877	0,9786	**0,9876**	0,0211	0,0170	<0,0000	236	38	<0,0000
SegFormer	0,0283	0,9887	0,0136	0,9929	0,9817	0,9938	0,9877	**0,9932**	0,0580	0,0411	<0,0000	650	92	<0,0000
SwinTransformer	0,0283	0,9909	0,0325	0,9911	0,9758	0,9938	0,9847	**0,9919**	0,0344	0,0232	<0,0000	385	52	<0,0000
SwinTransformerV2	0,0368	0,9905	0,0240	0,9911	1,0000	0,9691	0,9843	**0,9846**	0,0455	0,0299	<0,0000	509	67	<0,0000
VisionTransformer	0,0250	0,9939	0,0147	0,9964	0,9938	0,9938	0,9938	**0,9957**	0,0750	0,0442	<0,0000	840	99	<0,0000
ViTHybrid	0,0281	0,9909	0,0239	0,9893	0,9815	0,9815	0,9815	**0,9870**	0,2252	0,1000	<0,0000	2.522	224	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained SwinTransformer (UCSD Ped1)

Doğruluk

%99.11



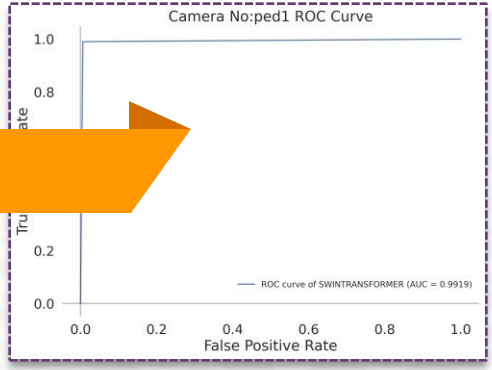


Kayıp

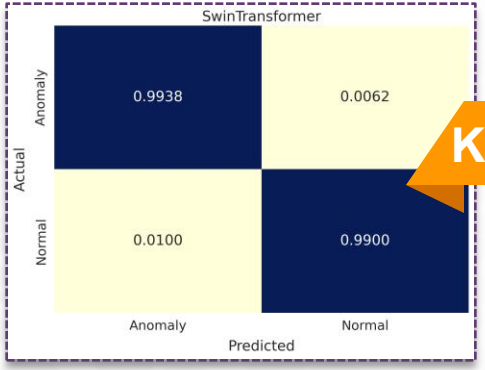
%3.25

AUC

%99.19



Karmaşıklık Matrisi



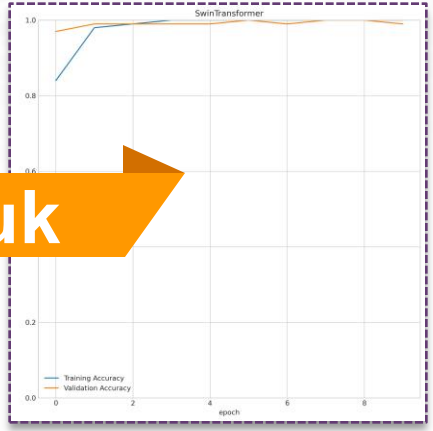
İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained Vision Transformers (UCSD Ped2)

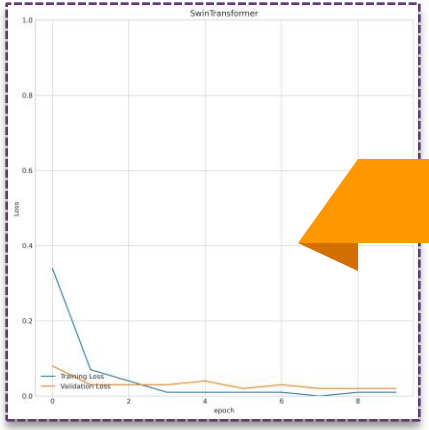
Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
ConvNeXT	0,0070	0,9974	0,0014	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0280	0,0137	<0,0000	102	10	<0,0000
EfficientFormer	0,0227	0,9937	0,0011	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0143	0,0137	<0,0000	52	10	<0,0000
FasterViT	0,0532	0,9885	0,0316	0,9891	1,0000	0,9697	0,9846	**0,9848**	0,0425	0,0356	<0,0000	155	26	<0,0000
LeViT	0,0624	0,9814	0,0638	0,9836	0,9697	0,9697	0,9697	**0,9763**	0,0112	0,0137	<0,0000	41	10	<0,0000
MobileViT	0,0356	0,9909	0,0077	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0233	0,0178	<0,0000	85	13	<0,0000
SegFormer	0,0287	0,9961	0,0301	0,9945	1,0000	0,9848	0,9924	**0,9924**	0,0625	0,0466	<0,0000	228	34	<0,0000
SwinTransformer	0,0233	0,9935	0,0081	0,9945	1,0000	0,9848	0,9924	**0,9924**	0,0359	0,0233	<0,0000	131	17	<0,0000
SwinTransformerV2	0,0366	0,9942	0,0084	0,9945	1,0000	0,9848	0,9924	**0,9924**	0,0557	0,0438	<0,0000	203	32	<0,0000
VisionTransformer	0,0287	0,9942	0,0274	0,9946	1,0000	0,9848	0,9924	**0,9925**	0,0792	0,0493	<0,0000	289	36	<0,0000
ViTHybrid	0,0559	0,9922	0,0184	0,9945	1,0000	0,9849	0,9925	**0,9924**	0,2270	0,1096	<0,0000	828	80	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
Fine-Tuning Pre-Trained SwinTransformer (UCSD Ped2)

Doğruluk

%99.45



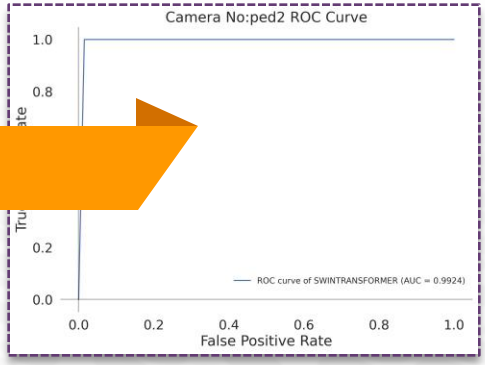


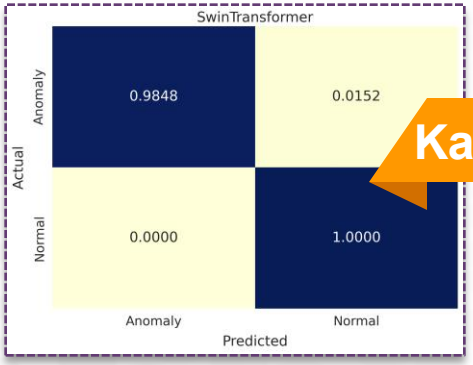
Kayıp

%0.81

AUC

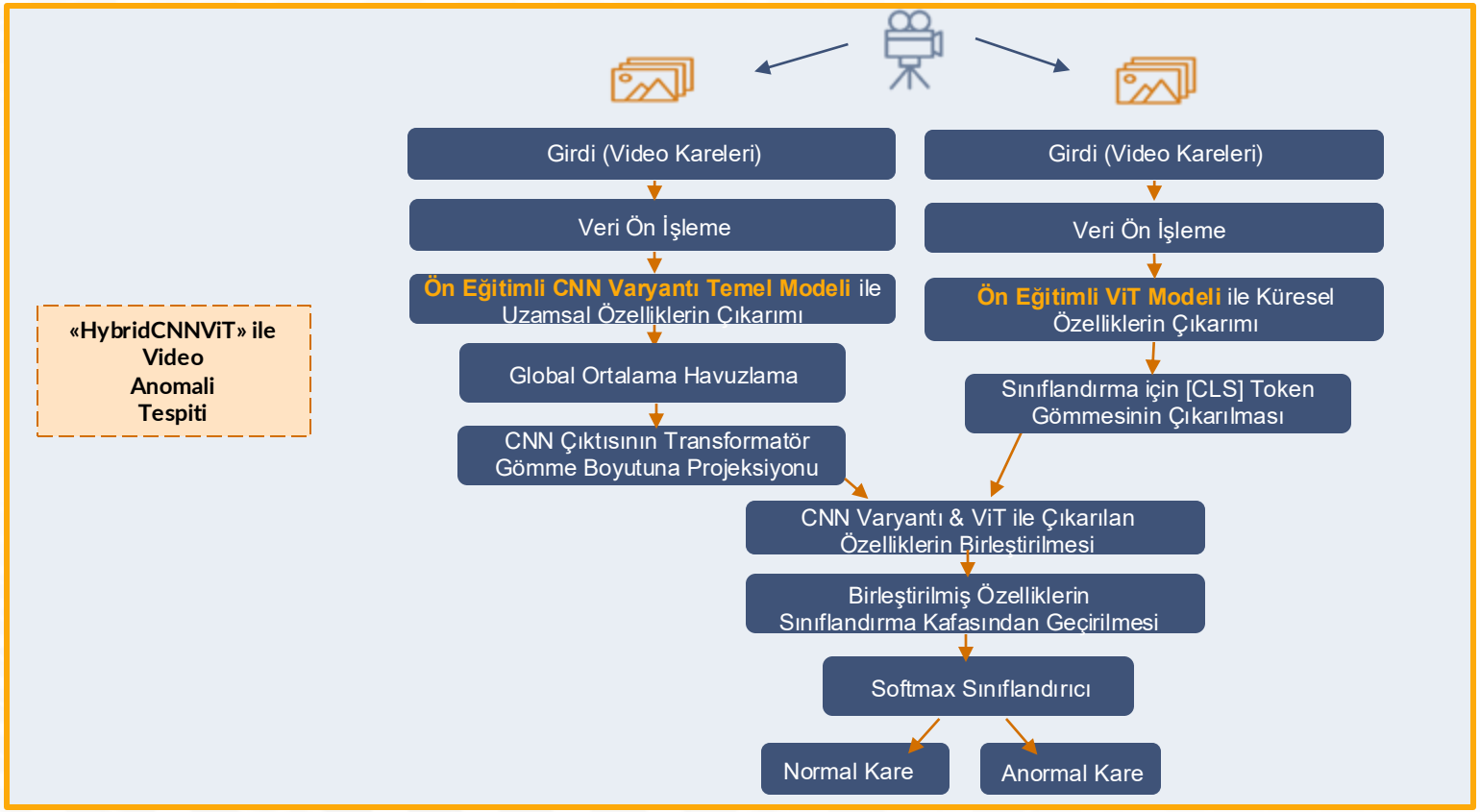
%99.24





Karmaşıklık Matrisi

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
HybridCNNViT Video Anomali Tespit Modeli



İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
HybridCNNViT'te Kullanılan Temel Modeller

VGG16

ResNet50

Xception

InceptionV3

EfficientNetB0

EfficientNetV2S

MobileNetV3Small

DenseNet121

NASNetLarge

ConvNeXtTiny

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
HybridCNNViT (50+150)

Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
VGG16	0,0053	0,9988	0,0367	0,9975	0,9982	0,9982	0,9982	**0,9971**	0,0671	0,0556	<0,0000	1.074	178	<0,0000
ResNet50	0,0016	0,9997	0,0055	0,9975	0,9982	0,9982	0,9982	**0,9971**	0,0617	0,0547	<0,0000	988	175	<0,0000
Xception	0,0050	0,9982	0,0371	0,9938	0,9963	0,9945	0,9954	**0,9933**	0,0705	0,0565	<0,0000	1.128	181	<0,0000
InceptionV3	0,0002	1,0000	0,0348	0,9975	0,9982	0,9982	0,9982	**0,9971**	0,1375	0,1381	<0,0000	2.201	442	<0,0000
EfficientNetB0	0,0010	0,9997	0,0111	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,0689	0,0590	<0,0000	1.102	189	<0,0000
EfficientNetV2S	0,0032	0,9997	0,0158	0,9975	0,9982	0,9982	0,9982	**0,9971**	0,0539	0,0419	<0,0000	863	134	<0,0000
MobileNetV3Small	0,0002	1,0000	0,0101	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,0613	0,0562	<0,0000	981	180	<0,0000
DenseNet121	0,0000	1,0000	0,0101	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,0502	0,0378	<0,0000	803	121	<0,0000
NASNetLarge	0,0006	0,9997	0,0060	0,9988	1,0000	0,9982	0,9991	**0,9991**	0,1317	0,0747	<0,0000	2.107	239	<0,0000
ConvNeXtTiny	0,0167	0,9940	0,0270	0,9913	1,0000	0,9872	0,9936	**0,9936**	0,0677	0,0465	<0,0000	1.084	149	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
HybridCNNViT (206+200)

Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
VGG16	0,0000	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,1198	0,1247	0,0013	2.111	392	1,0000
ResNet50	0,0000	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0616	0,0547	<0,0000	1.085	172	<0,0000
Xception	0,0000	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0519	0,0382	<0,0000	914	120	<0,0000
InceptionV3	0,0000	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0618	0,0554	<0,0000	1.089	174	<0,0000
EfficientNetB0	0,0008	0,9997	0,0001	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0623	0,0538	<0,0000	1.098	169	<0,0000
EfficientNetV2S	0,0000	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,1267	0,1044	0,0025	2.232	328	2,0000
MobileNetV3Small	0,0001	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0611	0,0573	<0,0000	1.076	180	<0,0000
DenseNet121	0,0000	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0539	0,0445	<0,0000	949	140	<0,0000
NASNetLarge	0,0000	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,2135	0,1444	0,0013	3.761	454	1,0000
ConvNeXtTiny	0,0001	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0901	0,0627	<0,0000	1.587	197	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
HybridCNNViT (132+800)

Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
VGG16	0,0003	0,9996	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0665	0,0546	<0,0000	847	139	<0,0000
ResNet50	0,0011	0,9996	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0446	0,0393	<0,0000	568	100	<0,0000
Xception	0,0001	1,0000	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0519	0,0393	<0,0000	661	100	<0,0000
InceptionV3	0,0008	0,9996	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0434	0,0353	<0,0000	553	90	<0,0000
EfficientNetB0	0,0010	0,9996	0,0001	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0436	0,0357	<0,0000	555	91	<0,0000
EfficientNetV2S	0,0003	0,9996	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0502	0,0393	<0,0000	639	100	<0,0000
MobileNetV3Small	0,0004	1,0000	0,0001	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0984	0,0805	<0,0000	1.253	205	<0,0000
DenseNet121	0,0010	0,9996	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,1228	0,1249	0,0016	1.563	318	1,0000
NASNetLarge	0,0021	0,9996	0,0000	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,2015	0,1249	0,0016	2.566	318	1,0000
ConvNeXtTiny	0,0065	0,9980	0,0045	0,9984	0,9932	1,0000	0,9966	**0,9990**	0,1385	0,0982	<0,0000	1.764	250	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
HybridCNNViT (CUHK Avenue)

Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
VGG16	0,0233	0,9931	0,0334	0,9870	0,9640	0,9241	0,9437	**0,9598**	0,0880	0,0893	0,0008	2.157	438	1,0000
ResNet50	0,0301	0,9916	0,0354	0,9861	0,9211	0,9655	0,9428	**0,9772**	0,0819	0,0887	0,0008	2.007	435	1,0000
Xception	0,0284	0,9926	0,0329	0,9935	0,9724	0,9724	0,9724	**0,9844**	0,0835	0,0775	0,0024	2.047	380	3,0000
InceptionV3	0,0214	0,9950	0,0291	0,9910	0,9467	0,9793	0,9627	**0,9860**	0,1164	0,1067	<0,0000	2.855	523	<0,0000
EfficientNetB0	0,0256	0,9931	0,0275	0,9902	0,9586	0,9586	0,9586	**0,9765**	0,0728	0,0775	<0,0000	1.784	380	<0,0000
EfficientNetV2S	0,0321	0,9930	0,0539	0,9894	0,9648	0,9448	0,9547	**0,9701**	0,0711	0,0732	<0,0000	1.743	359	<0,0000
MobileNetV3Small	0,0436	0,9908	0,0538	0,9886	0,9580	0,9448	0,9514	**0,9696**	0,0689	0,0773	0,0008	1.690	379	1,0000
DenseNet121	0,0261	0,9944	0,0333	0,9919	0,9856	0,9448	0,9648	**0,9715**	0,0781	0,0855	<0,0000	1.915	419	<0,0000
NASNetLarge	0,0287	0,9940	0,0393	0,9927	0,9658	0,9724	0,9691	**0,9839**	0,1043	0,0514	<0,0000	2.557	252	<0,0000
ConvNeXtTiny	0,0319	0,9910	0,0668	0,9845	0,9632	0,9034	0,9324	**0,9494**	0,0920	0,0857	<0,0000	2.257	420	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
HybridCNNViT (UCSD Ped1)

Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
VGG16	0,0313	0,9917	0,0280	0,9768	0,9257	1,0000	0,9614	**0,9837**	0,0522	0,0402	<0,0000	585	90	<0,0000
ResNet50	0,0147	0,9957	0,0068	0,9947	0,9818	1,0000	0,9908	**0,9962**	0,0439	0,0353	<0,0000	492	79	<0,0000
Xception	0,0223	0,9939	0,0075	0,9947	0,9818	1,0000	0,9908	**0,9962**	0,0511	0,0366	<0,0000	572	82	<0,0000
InceptionV3	0,0225	0,9935	0,0068	0,9929	0,9759	1,0000	0,9878	**0,9950**	0,0655	0,0514	<0,0000	734	115	<0,0000
EfficientNetB0	0,0075	0,9970	0,0022	1,0000	0,0000	1,0000	1,0000	**1,0000**	0,0587	0,0464	<0,0000	657	104	<0,0000
EfficientNetV2S	0,0397	0,9935	0,0252	0,9840	0,9581	0,9877	0,9726	**0,9851**	0,0505	0,0384	<0,0000	565	86	<0,0000
MobileNetV3Small	0,0303	0,9874	0,0258	0,9929	0,9877	0,9877	0,9877	**0,9913**	0,0402	0,0353	<0,0000	450	79	<0,0000
DenseNet121	0,0321	0,9891	0,0138	0,9964	0,9938	0,9938	0,9938	**0,9957**	0,0493	0,0393	<0,0000	552	88	<0,0000
NASNetLarge	0,0303	0,9900	0,0221	0,9947	0,9818	1,0000	0,9908	**0,9962**	0,1201	0,0661	<0,0000	1.345	148	<0,0000
ConvNeXtTiny	0,0487	0,9874	0,0685	0,9768	0,9357	0,9877	0,9610	**0,9800**	0,0814	0,0581	<0,0000	912	130	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
Performans İyileştirme
HybridCNNViT (UCSD Ped2)

Model	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy	Precision	Recall	F1 Score	AUC	Training Time/Frame (s)	Validation Time/Frame (s)	Prediction Time/Frame (s)	Training Time (s)	Validation Time (s)	Prediction Time (s)
VGG16	0,0099	0,9955	0,0141	0,9891	1,0000	0,9697	0,9846	**0,9848**	0,0631	0,0575	<0,0000	230	42	<0,0000
ResNet50	0,0101	0,9961	0,0035	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0573	0,0479	<0,0000	209	35	<0,0000
Xception	0,0159	0,9961	0,0292	0,9945	1,0000	0,9848	0,9924	**0,9924**	0,0653	0,0534	<0,0000	238	39	<0,0000
InceptionV3	0,0219	0,9935	0,0089	0,9945	1,0000	0,9848	0,9924	**0,9924**	0,0787	0,0479	<0,0000	287	35	<0,0000
EfficientNetB0	0,0198	0,9961	0,0085	0,9945	1,0000	0,9848	0,9924	**0,9924**	0,0633	0,0493	<0,0000	231	36	<0,0000
EfficientNetV2S	0,0395	0,9955	0,0026	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0672	0,0534	<0,0000	245	39	<0,0000
MobileNetV3Small	0,1034	0,9589	0,0956	0,9672	0,9839	0,9242	0,9531	**0,9578**	0,0332	0,0274	<0,0000	121	20	<0,0000
DenseNet121	0,0180	0,9948	0,0014	1,0000	1,0000	1,0000	1,0000	**1,0000**	0,0472	0,0342	<0,0000	172	25	<0,0000
NASNetLarge	0,0241	0,9948	0,0436	0,9945	1,0000	0,9848	0,9924	**0,9924**	0,0990	0,0425	<0,0000	361	31	<0,0000
ConvNeXtTiny	0,0135	0,9961	0,0086	0,9945	1,0000	0,9848	0,9924	**0,9924**	0,0828	0,0589	<0,0000	302	43	<0,0000

İŞ PAKETİ 6 (15-18 Ay)
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RESEARCH ARTICLE

Enhancement of Video Anomaly Detection Performance Using Transfer Learning and Fine-Tuning

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ABSTRACT The use of surveillance cameras is a common solution that addresses the need to provide security and manage urban traffic that arises due to the increasing population in cities. As the number of surveillance cameras rises, video streams that create big data are recorded. The analysis of video streams collected from those traffic surveillance cameras and the automatic detection of unusual, suspicious events, as well as a range of harmful activities, have become crucial because it is impossible to observe, analyze, and comprehend the contents of these movies using human labor. Recent studies have shown that deep learning (DL)-based artificial intelligence (AI) techniques, particularly machine learning (ML) systems, are used in video anomaly detection (VAD) studies. In this study, an efficient frame-level VAD method is proposed based on transfer learning (TL) and fine-tuning (FT) approach, and anomalies were detected using 20 popular convolutional neural network (CNN)-based DL models where variants of VGG, Xception, MobileNet, Inception, EfficientNet, ResNet, DenseNet, NASNet, and ConvNeXt base models were trained via the TL and FT approaches. The proposed approach was tested using the CUHK Avenue, UCSD Ped1, and UCSD Ped2 datasets, and the performances of the models were measured via area under curve (AUC), accuracy, precision, recall, and F1-score metrics. The highest AUC scores measured were 100%, 100%, and 98.41% for the UCSD Ped1, UCSD Ped2, and CUHK Avenue datasets, respectively. Compared to existing techniques in the literature, experimental results show that the suggested method offers state-of-the-art VAD performance.

INDEX TERMS CUHK avenue, deep learning, fine-tuning, transfer learning, UCSD Ped1, UCSD Ped2, video anomaly detection.

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2-4 Mayıs 2024 Ankara, Türkiye

Leveraging Transformer Models for Video Anomaly Detection: A Survey

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Abstract

First employed in the field of natural language processing for machine translation tasks, transformer is a type of deep neural network that is based on the self-attention mechanism, and is capable of capturing long-term dependencies. Transformer has high data representation capabilities, which makes it useful for computer vision (CV) applications. In this paper, we examined contemporary vision transformer-based methods for video anomaly detection (VAD). We explored transformer models used in VAD methods and vision transformers utilized in CV applications. In addition, we discussed the benefits, drawbacks, and current limitations of transformer architecture, and provided directions for further research in relation to VAD using vision transformers.

Keywords: Transformer; vision transformer; video anomaly detection; attention mechanism; computer vision

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REVIEW

An overview of transformers for video anomaly detection

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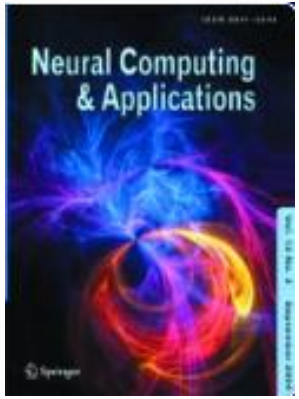
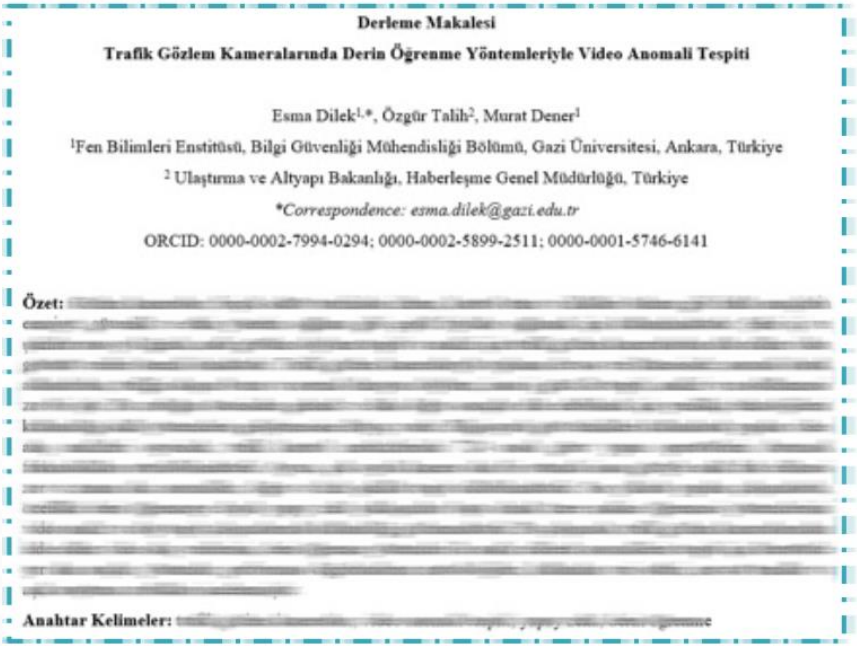
Abstract
Transformer is a kind of deep neural network that relies on the technique of self-attention and used initially in the field of natural language processing. Scientists use transformer for computer vision (CV) applications because of its good data representation capabilities. Transformer-based models yield similar performance or surpass other network architectures, including convolutional and recurrent neural networks, in a variety of visual benchmarks. In this work, we investigate the methods for video anomaly detection (VAD) using vision transformer models in the recent literature. The main topics we explore comprise vision transformers used in CV applications with a special focus on VAD methods leveraging transformer architecture. We also briefly present anomaly detection methods based on transformers. Additionally, we address the advantages, challenges and current limitations of the transformer architecture as well as potential solutions to address the technical challenges. In the concluding section of this study, we offer avenues for further investigation concerning the use of vision transformers in VAD tasks.

Keywords Transformer · Video anomaly detection · Vision transformer · Anomaly detection · Computer vision



SPRINGER NATURE

DEĞERLENDİRME AŞAMASINDA OLAN AKADEMİK ÇALIŞMALAR (2024)



Derleme Makalesi

Trafik Gözlem Kameralarında Derin Öğrenme Yöntemleriyle Video Anomali Tespiti

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Özet:

Anahtar Kelimeler:

GAZİ ÜNİVERSİTESİ MÜHENDİSLİK MİMARLIK FAKÜLTESİ DERGİSİ
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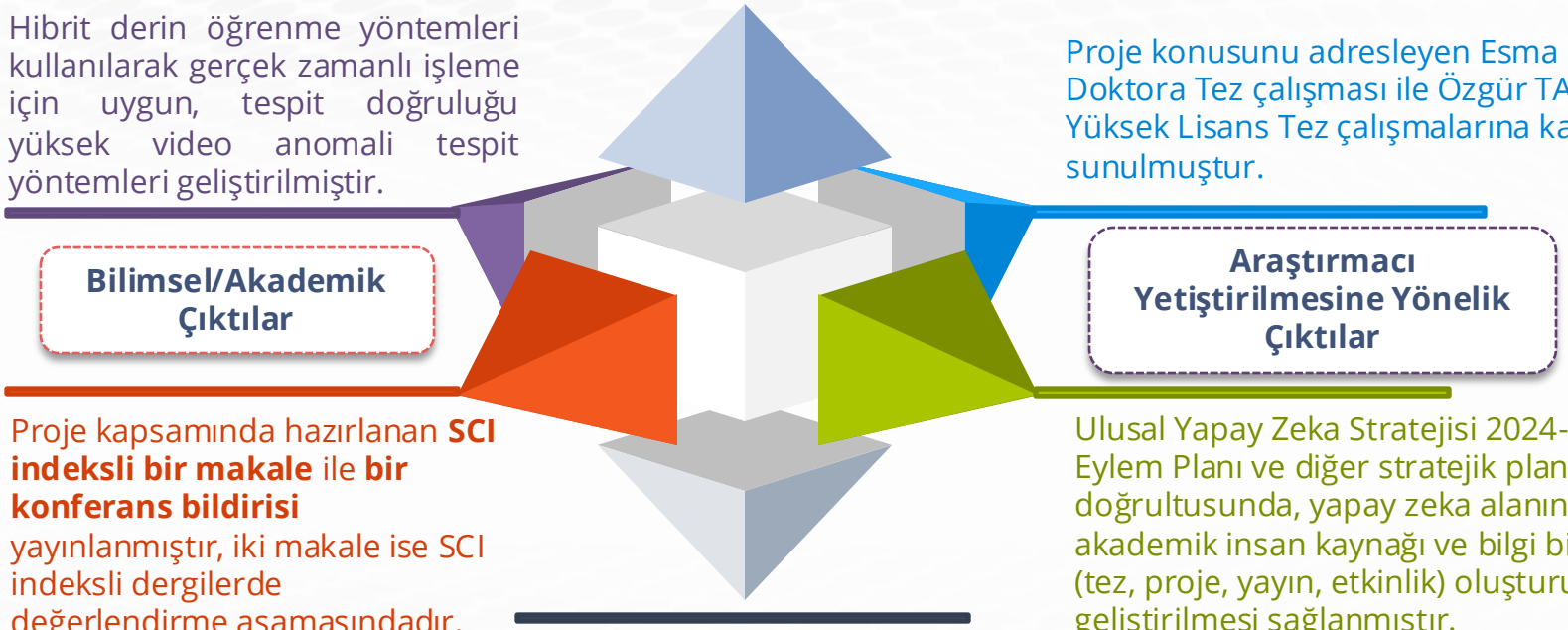
SONUÇLAR

Hibrit derin öğrenme yöntemleri kullanılarak gerçek zamanlı işleme için uygun, tespit doğruluğu yüksek video anomali tespit yöntemleri geliştirilmiştir.

Proje konusunu adresleyen Esma DİLEK'in Doktora Tez çalışması ile Özgür TALİH'in Yüksek Lisans Tez çalışmalarına katkı sunulmuştur.



Proje kapsamında hazırlanan **SCI indeksli bir makale** ile **bir konferans bildirisi** yayınlanmıştır, iki makale ise SCI indeksli dergilerde değerlendirme aşamasındadır.

Ulusal Yapay Zeka Stratejisi 2024-2025 Eylem Planı ve diğer stratejik plan hedefleri doğrultusunda, yapay zeka alanında akademik insan kaynağı ve bilgi birikiminin (tez, proje, yayın, etkinlik) oluşturulması ve geliştirilmesi sağlanmıştır.

Yerli teknoloji geliştirici firmalarla iş birliği yapılarak ticari bir ürüne dönüştürülebilecek, trafik kontrol merkezlerinde çalışan uygulamalarda faydalanılabilecek bir yapay zeka modeli geliştirilmiştir.

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KAYNAKLAR

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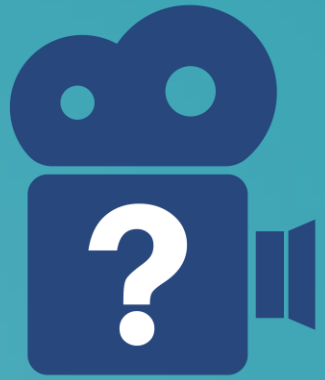
Teşekkür Ederiz



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