CHUQUR O‘RGANISH ASOSIDA TASVIRLARDAN PM2.5 KONSENTRATSIYASINI BASHORATLOVCHI CNN–FNN REGRESSIYA MODELI

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K E Y W O R D S

PM2.5, havo sifati, chuqur o‘rganish, konvolyutsion neyron tarmoq, to‘liq bog‘langan neyron tarmoq, EfficientNetV2B0, regressiya modeli

A B S T R A C T

Atmosfera havosidagi mayda dispers zarrachalar, xususan PM2.5, aholi salomatligi va ekologik xavfsizlikka bevosita ta’sir ko‘rsatadigan muhim ifloslantiruvchi omillardan biridir. Mazkur maqolada havo muhitining vizual belgilariga tayangan holda PM2.5 konsentratsiyasini avtomatik baholashga mo‘ljallangan CNN–FNN regressiya modeli taklif etiladi. Tadqiqotda Hindiston va Nepal hududlarida olingan 224×224 o‘lchamli 12240 ta tasvir hamda ularga mos PM2.5 qiymatlaridan foydalanildi. Tasvirlardan chuqur xususiyatlarni ajratish uchun ImageNet ma’lumotlar to‘plamida oldindan o‘qitilgan EfficientNetV2B0 arxitekturasi qo‘llanildi, hosil qilingan 1280 o‘lchamli belgilar vektori esa to‘liq bog‘langan neyron tarmoq orqali regressiya masalasi sifatida qayta ishlanadi. Tajriba natijalarida normallashtirilgan birliklarda Test MAE = 0.072 va Test MSE = 0.011 ko‘rsatkichlari olindi. Natijalar tasvirga asoslangan yondashuv havo sifatini kontaktlarsiz monitoring qilish, sensor tarmoqlari yetarli bo‘lmagan hududlarda PM2.5 darajasini tezkor baholash va kelgusida multimodal ekologik monitoring tizimlariga integratsiya qilish uchun istiqbolli ekanligini ko‘rsatadi.

1. Kirish

So‘nggi yillarda atmosfera havosining ifloslanishi inson salomatligi, ekologiya va iqlim o‘zgarishiga bevosita ta’sir qiluvchi global muammo sifatida e’tirof etilmoqda. Ayniqsa, PM2.5 (diametri 2.5 mikrondan kichik bo‘lgan zarrachalar) inson nafas yo‘llariga chuqur kirib, surunkali kasalliklar keltirib chiqaradi. An’anaviy usullar — maxsus stansiyalar va sensorga asoslangan o‘lchov tizimlari — yuqori aniqlikka ega bo‘lsada, ularning qamrovi tor va texnik xizmat xarajatlari yuqori[1]. So‘nggi yillarda sun’iy intellekt va chuqur o‘rganish (Deep Learning) asosida havo sifatini tasvirlar yordamida baholash yo‘nalishiga qiziqish kuchaydi[2]. Chunki tasvirlarda havoning loyqaligi, tuman, yorug‘lik diffuziyasi va atmosfera tarqalish effektlari mavjud bo‘lib, ular PM2.5 konsentratsiyasi bilan bevosita bog‘liq[3]. Shu bois, ushbu ishda tasvirdan PM2.5 bashoratlovchi regressiya modeli ishlab chiqildi.

So‘nggi o‘n yillikda havo sifatini aniqlash bo‘yicha ko‘plab ilmiy tadqiqotlar olib borilgan[4]. Dastlabki ishlarda asosan fizik sensorlar va meteorologik o‘lchov stansiyalaridan olingan ma’lumotlarga tayanilgan[5]. Masalan, AQShning *EPA (Environmental Protection Agency)* va Xitoyning *CAMS* tizimlari real vaqtda PM2.5 konsentratsiyasini o‘lchash uchun keng ko‘lamli sensorga asoslangan tarmoqlarni tashkil etgan[6]. Biroq bu usullar infratuzilma va texnik xizmat ko‘rsatish xarajatlari tufayli global miqyosda cheklangan.

Keyingi yillarda masofaviy zondlash (Remote Sensing) texnologiyalari jadal rivojlandi va sun’iy yo‘ldosh tasvirlari orqali havodagi zarrachalar miqdorini baholash imkoniyati paydo bo‘ldi[7]. Masalan:

- NASA MODIS va Sentinel-2 ma’lumotlari asosida PM2.5 ni aerosol optik zichlik (AOD)

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orqali regressiya yo‘li bilan baholovchi modellardan foydalanilgan[8].
- Landsat 8 tasvirlarida spektral indekslar (NDVI, NDBI, MNDWI) yordamida havo sifatining mahalliy o‘zgarishlarini kuzatish ishlari olib borilgan[9].

Biroq bu yondashuvlarda faqat fizik parametrlar ishlatilgani sababli, havoning vizual belgilarini (masalan, tumanlik, shaffoflik, yorug‘lik tarqalishi) bevosita tahlil qilish imkoniyati yo‘q edi. Shuning uchun so‘nggi tadqiqotlarda tasvirga asoslangan sun’iy intellekt yondashuvlari keng qo‘llanilmoqda[12]. Masalan:

- *Zhang va boshq. (2020)* tasvirlardan PM2.5 ni bashoratlash uchun ResNet50 modelini qo‘llab, 0.85 aniqlikka erishgan[11].
- *Li va boshq.* (2022) *DenseNet* arxitekturasidan foydalangan holda turli ob-havo sharoitlarida olingan shahar tasvirlaridan PM2.5 ni regressiya yo‘li bilan taxmin qilgan[10].
- *Ma va boshq. (2020)* esa multimodal yondashuv taklif etib, tasvirdan olingan xususiyatlarni meteorologik ma’lumotlar (harorat, shamol tezligi, namlik) bilan birlashtirgan va bashorat aniqligini 12% ga oshirgan[13].

2. Usullar

Tadqiqotda Hindiston va Nepal hududlarida olingan tasvirlar to‘plami hamda har bir tasvirga mos PM2.5 qiymatlari mavjud bo‘lgan CSV jadvalidan foydalanildi. Ma’lumotlar to‘plamida jami 12240 ta tasvir mavjud bo‘lib, ular 224×224 piksel o‘lchamga keltirilgan. Tasvirlarda asosan osmon, shahar manzarasi, tumanlilik va atmosfera shaffofligini ifodalovchi vizual belgilar aks etgan. CSV faylda tasvir nomi, joylashuv, vaqt, PM2.5 va boshqa ekologik ko‘rsatkichlar keltirilgan.

Jadval 1.

Tadqiqotda foydalanilgan ma’lumotlar to‘plamining umumiy tavsifi

Ko‘rsatkich	Tavsif
Tasvirlar soni	12240 ta
Tasvir o‘lchami	224×224 piksel
Hududlar	Hindiston va Nepal
Nishon o‘zgaruvchi	PM2.5 konsentratsiyasi
Modelga kiritish	Tasvirlardan ajratilgan 1280 o‘lchamli belgilar vektori
O‘qitishda foydalanilgan namuna	3000 ta tasodifiy tanlangan namuna

IND_and_Nep_AQI_Dataset.csv

	0	1	2	3	4	5	6	7	8	9	10	11	12	
0	Location	Filename	Year	Month	Day	Hour	AQI	PM2.5	PM10	O3	CO	SO2	NO2	AQI_Class
1	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-9.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
2	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-8.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
3	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-7.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
4	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-6.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
5	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-5.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
6	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-4.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
7	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-3.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
8	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-2.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
9	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-18.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
10	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-17.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
11	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-16.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
12	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-15.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
13	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-14.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
14	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-13.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
15	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-12.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
16	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-11.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
17	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-10.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
18	Biratnagar, Nepal	BRI_Un_2023-02-02- 12.00-1.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
19	Biratnagar, Nepal	BIR_UNH_VF_2023-02-02- 12.00-3-9.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
20	Biratnagar, Nepal	BIR_UNH_VF_2023-02-02- 12.00-3-8.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
21	Biratnagar, Nepal	BIR_UNH_VF_2023-02-02- 12.00-3-77.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
22	Biratnagar, Nepal	BIR_UNH_VF_2023-02-02- 12.00-3-76.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
23	Biratnagar, Nepal	BIR_UNH_VF_2023-02-02- 12.00-3-75.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy
24	Biratnagar, Nepal	BIR_UNH_VF_2023-02-02- 12.00-3-74.jpg	2023	2	2	12:00	158	70.08	100.82	58.89	0.49	4.4	1.04	d_Unhealthy

Rasm 1. PM2.5 ko‘rsatkichlari berilgan ma’lumotlar jadvali namunasi

Modelni qurish jarayoni ikki asosiy bosqichdan iborat bo‘ldi. Birinchi bosqichda EfficientNetV2B0 modeli yordamida tasvirlardan chuqur xususiyatlar ajratildi[14]. Ushbu arxitektura ImageNet to‘plamida oldindan o‘qitilgani sababli, rang, tekstura, chekka, gradient, kontrast va murakkab vizual shakllarni samarali ifodalash imkonini beradi[15]. CNN qismidan olingan 1280 o‘lchamli belgilar vektori har bir tasvirning havo

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sifati bilan bog‘liq yashirin vizual xususiyatlarini raqamli ko‘rinishda aks ettiradi[16].

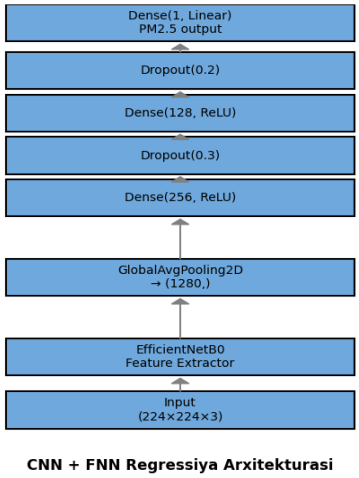
Ikkinchi bosqichda ajratilgan belgilar FNN regressiya blokiga uzatildi. PM2.5 qiymatlari 0–1 oraliqqa normallashtirildi, bu esa o‘qitish jarayonida gradientlarning barqarorligini ta’minlash va yo‘qotish funksiyasini kamaytirishga xizmat qildi[17]. Overfitting xavfini kamaytirish uchun Dropout qatlamlaridan foydalanildi. Model Mean Absolute Error (MAE) yo‘qotish funksiyasi asosida o‘qitildi.



Rasm 2. Turli PM2.5 qiymatlariga ega tasvirlar namunasi

Taklif etilgan CNN–FNN arxitekturasi

Taklif etilgan arxitekturada CNN qismi tasvirdan informativ xususiyatlarni ajratadi, FNN qismi esa ushbu belgilar asosida PM2.5 qiymatini sonli natija sifatida bashoratlaydi[18]. Modelning regressiya bloki quyidagi qatlamlardan tashkil topgan: 256 neyronli Dense qatlam va ReLU aktivatsiya funksiyasi, 0.3 koeffitsiyentli Dropout qatlami, 128 neyronli Dense qatlam va ReLU aktivatsiya funksiyasi, yakuniy 1 neyronli linear chiqish qatlami. Linear chiqish tanlanishi PM2.5 qiymati uzluksiz sonli kattalik ekanligi bilan izohlanadi[19].

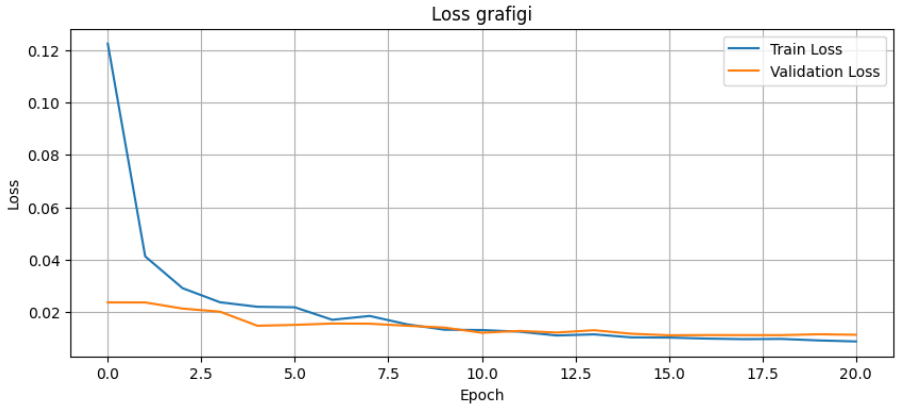


Rasm 3. Taklif etilgan CNN–FNN regressiya modelining arxitekturasi

3. Natijalar va muhokama

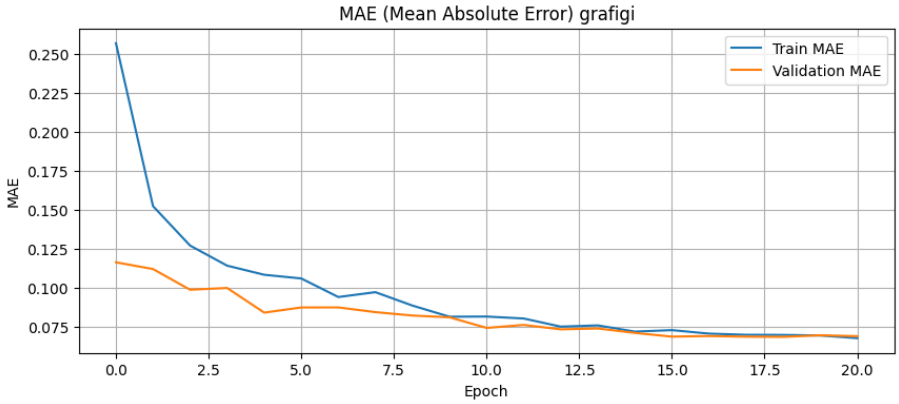
Tajriba jarayonida modelga kiruvchi ma’lumot sifatida tasvirlar, chiquvchi qiymat sifatida esa PM2.5 konsentratsiyasi berildi. O‘qitish va validatsiya grafiklari modelning dastlabki epoxalarda tez o‘rganishini, keyingi bosqichlarda esa yo‘qotish funksiyasi sekin-asta barqarorlashganini ko‘rsatdi[20]. Train loss va validation loss chiziqlarining bir-biriga yaqinlashishi modelning umumiy tendensiyalarni o‘rganganini bildiradi.

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Rasm 4. O‘qitish va validatsiya bosqichidagi yo‘qotish funksiyasi grafigi

Model normallashtirilgan birliklarda Test MAE = 0.072 va Test MSE = 0.011 natijalariga erishdi. MAE qiymatining nisbatan kichikligi model o‘rtacha absolut xatoni kamaytirishga muvaffaq bo‘lganini ko‘rsatadi. MSE qiymati esa katta xatolarga sezgir bo‘lgani sababli, ayrim yuqori ifloslanish holatlarida bashorat chetlanishlari mavjudligini ko‘rsatishi mumkin. Bu holat datasetdagi yuqori PM2.5 qiymatlari kamroq uchrashi, tasvirlarning yorug‘lik sharoiti turlicha bo‘lishi yoki havo ifloslanishining faqat vizual belgilar orqali to‘liq ifodalanmasligi bilan bog‘liq bo‘lishi ehtimol.



Rasm 5. MAE ko‘rsatkichining epoxalar bo‘yicha o‘zgarishi

Vizual tahlil shuni ko‘rsatadiki, model havoning umumiy shaffofligi, osmon rangining xiralashuvi va tumanlilik kabi belgilar asosida PM2.5 darajasini taxmin qila oladi. Biroq yuqori ifloslanish yoki yorug‘lik keskin o‘zgargan holatlarda bashorat aniqligi pasayishi mumkin. Shu jihatdan, taklif etilgan model mustaqil monitoring vositasi sifatida emas, balki sensor, meteorologik parametrlar va masofaviy zondlash ma’lumotlari bilan birlashtirilgan multimodal tizim tarkibida yanada samarali ishlashi mumkin.

4. Xulosa

Ushbu maqolada tasvirlar asosida PM2.5 konsentratsiyasini bashoratlash uchun CNN–FNN regressiya modeli ishlab chiqildi. EfficientNetV2B0 yordamida tasvirlardan chuqur xususiyatlar ajratildi va ular to‘liq bog‘langan neyron tarmoq orqali sonli PM2.5 qiymatini baholashga yo‘naltirildi. Olingan natijalar tasvirga asoslangan yondashuv havo sifatini baholashda amaliy ahamiyatga ega ekanligini ko‘rsatdi.

Tadqiqot natijalari quyidagi ilmiy-amaliy xulosalarni beradi: birinchidan, havo muhitining vizual belgilari PM2.5 konsentratsiyasi haqida muhim axborot tashiydi; ikkinchidan, transfer learning asosidagi CNN arxitekturalari kichikroq o‘qitish resurslari sharoitida ham samarali belgilar ajratishi mumkin; uchinchidan, FNN regressiya

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bloki PM2.5 qiymatini uzluksiz kattalik sifatida baholashda sodda va samarali yechim hisoblanadi.

Kelgusida model aniqligini oshirish uchun dataset hajmini kengaytirish, yuqori PM2.5 qiymatlariga ega tasvirlar sonini muvozanatlashtirish, yorug‘lik va rang diapazonlarini standartlashtirish, meteorologik atributlarni multimodal kirish sifatida qo‘shish hamda EfficientNetV2, ResNet, Vision Transformer va CNN–LSTM kabi arxitekturalarni solishtirma tahlil qilish maqsadga muvofiqdir. Umuman olganda, taklif etilgan yondashuv sensor tarmoqlari yetarli bo‘lmagan hududlarda havo sifatini tezkor, arzon va kontaktlarsiz baholash imkoniyatini kengaytiradi.

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